Microsimulation modelling of agricultural and spatial economics: Income, investment, and farmer behavior

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Microsimulation Modelling of Agricultural and Spatial Economics:

Income, Investment, and Farmer Behavior

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Thesis submitted for the Degree of Doctor of Philosophy

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Declaration

I declare that this thesis has not previously been submitted as an exercise for a degree at the University of Galway or any other University, and I further declare that the work embodied in it is my own, except where acknowledged and referenced.

Dilovar Haydarov

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Nomenclature

AES	Agri-Environmental Scheme
CAP	Common Agricultural Policy
CoA	Census of Agriculture
CSO	Central Statistics Office
DAFM	Department of Agriculture Food and the Marine
EDs	Electoral Districts
EPA	Environmental Protection Agency
EU	European Union
FOA	Food and Agriculture Organisation of the UN
FFI	Family Farm Income
GO	Gross Output
Ha.	Hectare
IFA	Irish Farmers’ Association
Kg	Kilogram

LU	Livestock Unit
NFS	National Farm Survey
REDP	Rural Economy Development Programme
SMILE	Simulation Model of the Irish Local Economy
UAA	Utilizable Agricultural Area

Abstract

This thesis delves into the impact of natural capital attributes, such as soil quality, continentality, and environmental factors like rainfall and temperature, on the farm market gross margin. These factors vary geographically, affecting farm productivity and expenses differently based on location. To tackle this spatial diversity in natural capital, a model integrating physical, human, and natural capital within a geospatial microsimulation framework is utilized. By analyzing agricultural administrative and National Farm Survey data, the model captures agronomic disparities stemming from natural capital conditions in Ireland. The inclusion of natural capital drivers leads to notable adjustments in simulated agricultural incomes nationwide, with market gross margin per hectare rising in the South and South-East but declining in the Midlands and parts of the North. The main reason for spatial heterogeneity could be that the South and part of the South-East have relatively better natural capital, including improved soil quality compared to the North and part of the Midlands.

Recognizing the heterogeneity in natural capital unveils increased income variability, particularly among districts, highlighting the substantial influence of natural capital on farm income and stressing the importance of considering localized environmental and agronomic factors. It was found that there is greater variation in income within districts compared to the variation in income between areas when natural capital is taken into account.

Furthermore, while previous researches have focused on individual aspects of adopting practices for optimizing natural resource use to support sustainable agricultural intensification, there is a lack of comprehensive literature examining how various factors such as farm demographics, behavioral drivers, cost-benefit analyses, and agronomic needs for implementing nutrient management practices may differ based on farms' environmental contexts. A part of this thesis aims to explore the correlation between recognizing the need for liming and intending to lime, investigating potential drivers behind this relationship in the context of Ireland. Drawing on data sources like national farm surveys and spatial datasets of Irish farms and soils, the research employs statistical matching techniques alongside regression analyses. Results indicate a strong likelihood that farmers recognizing the need to lime due to low soil pH also intend to lime. Factors such as perceived behavioral controls, subjective norms, perceived resources, education levels, and age categories play significant roles in influencing farmers' intentions regarding lime application. This study sheds light on the complex interplay of behavioral factors impacting farmers' decisions on lime management practices within specific environmental settings.

Additionally, financial management is essential for agricultural sustainability amidst economic uncertainties. This work of the thesis introduces a spatially enhanced tool designed to improve farm financial planning for less financially active farmers by leveraging a spatial microsimulation approach based on the SMILE model. Also, utilizing data from Teagasc's National Farm Survey spanning 2001-2014, this tool offers detailed benchmarking information at the townland level to enhance financial planning effectiveness compared to regional or national data. By simplifying financial data input processes and providing tailored insights at a local level, this tool aims to encourage greater engagement in economic planning among small-scale farmers.

Finally, in pursuit of economically sustainable farms, managing various factors affecting output and costs is crucial. This study investigates the impact of investment changes on farm output and costs in Ireland using Deep Neural Networks with data from pastoral-based livestock systems surveys spanning 1996-2018. Results show that increasing investments by 10% leads to varying effects on gross output across different deciles of Irish farmers, emphasizing the importance of strategic investment decisions for agricultural productivity and cost management.

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List of publications

Accepted/Published papers

Paper 1/Chapter 4: Haydarov, D., O'Donoghue, C., Ryan, M., Zhang, C., 2024. Local natural capital influences on the spatial distribution of farm incomes. *International Journal of Microsimulation, 17*(1).

Paper 2/Chapter 5: Haydarov, D., & Zhang, C., 2023. The Marginal Effect of Investment in Machinery, Livestock, and Buildings on Irish Agricultural Output and Costs. *International Journal of Agricultural Economics, 8*(6), 305-314.

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Paper 4/Chapter 7: Haydarov, D., Zhang, C., & O'Donoghue, C., 2024. The Importance of Spatial Disaggregation in Providing Agricultural Market Outlook Advice.

Soon to be submitted paper

Paper 3/Chapter 6: Haydarov, D., O'Donoghue, C., Ryan, M., Zhang, C., 2024. A spatial analysis of farmers' intentions to adopt nutrient management practices – a case study of soil pH management in Ireland.

1. CHAPTER ONE: Introduction

1.1. Background and Context

Agriculture represents a significant lands-based sector heavily reliant on environmental conditions such as weather, soil, altitude, and temperature. However, in grass-based outdoor livestock systems, agronomic and environmental factors like rainfall, temperature, grass growth, and soil type play a critical role in determining farm profitability. For instance, extended winters reduce outdoor grazing days, leading farmers to incur additional expenses for animal feed.

Agriculture encompasses environmental, behavioral, and policy dimensions. Agricultural production largely depends on externally determined environmental conditions, with farmers' production influenced by available physical resources, technology, and environmental factors. Limited data sets collecting detailed information on environmental conditions raise concerns about potential omitted variable bias, as farmers' input choices respond partly to environmental conditions, leading to adjustments in commonly measured inputs like labor, land, and fertilizer use.

Understanding the impact of differential agronomic conditions and grass growth nationwide requires linking them to farm systems, size, and animal demographics (Haydarov et al., 2024). Given the interconnectedness of components within the biosphere, understanding causation and the degree of effect of explanatory variables is crucial. Land exerts significant influence on stocking density, with access to more grazing area enabling higher animal numbers. Meanwhile, changes in yield primarily result from genetic technologies, enhancing output through livestock breeding. Moreover, land with better environmental properties tends to be more productive than areas with natural constraints.

Agriculture, including arable and pastoral farming, relies on environmental conditions like weather, soil, altitude, and temperature. In livestock farming, agronomic factors determine pasture quality and quantity, impacting farm income and costs. The productivity of arable crops is often explained by factors such as temperature, irrigation, and crop characteristics.

Temperature significantly influences plant growth, with crops like maize and ryegrass exhibiting optimal growth responses at specific temperature ranges. Temperature extremes negatively affect crop yields and livestock activity, subsequently reducing milk and meat supply.

Access to water and soil moisture levels drive crop and grass growth, as water is essential for physical growth and photosynthesis. Land irrigation or rainfall can benefit farmers, with temperature affecting plant water needs. Soil composition varies across regions and significantly influences crop yield, with soil nutrients and fertility playing crucial roles. Also, it is worth mentioning that small farms, particularly those located in relatively poor soil quality areas, may need additional financial support to remain economically viable, as suggested by Atzori et al. (2015).

The main chemical nutrients required for crop growth are nitrogen, phosphorus, and potassium, sourced from the soil, chemical fertilizers, organic manures, or fixation from the atmosphere. Soil types classified based on characteristics like pH, nutrient properties, and fertility influence grass growth rate, cover, continentality, mean rain, and temperature. Better soil quality enables higher carrying capacity and grass yield.

Behavioral drivers such as the intention to adopt nutrient management practices influence farm economic returns, with the amount of nutrients required varying based on environmental characteristics like rainfall and temperature. This thesis will explore the spatial, economic, and behavioral drivers of nutrient management practices from the perspective of lime as a soil pH stabilizer.

Studies analysing factors impacting farmers' intention to follow nutrient management planning often overlook spatial and cost-benefit considerations. Understanding the economic aspect of nutrient management planning, including financial yield and spatial variability, is crucial for informed decision-making. Managing certain nutrients, such as phosphorus, is a priority for government officials because it relates to environmental sustainability (Macintosh et al., 2019).

Outdoor farming systems heavily rely on grass growth and yield, influenced by spatial environmental factors, nutrient management practices, and farmers' behaviour. Therefore, the predominantly outdoor farming systems in Ireland serve as a case study, with all farming systems' values combined and analysed per farm rather than per system.

Understanding the factors that influence farm income (Fayama et al., 2022; Junaidu et al., 2021) due to investments is crucial for farmers seeking to maximize their profits and manage their expenses. Farm profit is determined as the difference between farm output and costs. Knowing these influencing factors can serve as a valuable decision-making tool for farmers and agricultural policymakers. For instance, they may need to consider influencing certain farm variables, such as investment (Ouedraogo et al., 2021) in livestock, buildings, or machinery. Additionally, when farmers have incentives to increase their farm area or make environmentally conscious decisions like reducing machinery usage to decrease pollution, understanding the impact of these changes on farm output and costs becomes crucial.

1.2. Aim and objectives

The local environmental context is crucial for farm-level profitability. However, analyzing the differential effects of various environmental contexts on economic and environmental outcomes is challenging due to the scarcity of datasets incorporating both economic and environmental variables. Literature shows instances where analyses overcame this challenge by employing microsimulation techniques to integrate economic and environmental issues associated with agricultural production and its local context (Morrissey et al., 2008). However, existing models do not fully incorporate the detailed agronomic and environmental characteristics at the local level.

Therefore, this thesis aims to test the hypothesis of incorporating agronomic variables into a spatial farm-level microsimulation model to enhance its precision. By including agronomic variables, we aim to establish a spatial income distribution consistent with local environmental drivers. Achieving this requires a method to either sample or adjust agronomic variables. When sampling from survey data to census aggregates, one may encounter the challenge of cell size limitation in the survey dataset, hindering the availability of required variable observations. Hence, instead of a sampling technique, a simulation approach to adjust agronomic and environmental variables will be utilized. Thus, this thesis extends previous developments of a spatial farm-level microsimulation model to adjust specific farm characteristics to the local spatial environment of individual farms.

In reality, the environmental context of individual farms varies considerably, necessitating the consideration of spatial heterogeneity within agronomic variables. Therefore, local environmental conditions will be incorporated using variables traditionally used to calculate farm performance, such as output per hectare, number of animals per hectare, cost, and farm characteristics. This will result in a model adjusted to the localized agronomic characteristics of individual farms. Adjusting localized agronomic and environmental factors will improve the spatial accuracy of estimates of farm profitability in different locations.

Enhancing the precision of the spatial farm-level model is particularly important for ex ante policy analysis, where the accuracy of spatial variability is crucial, and spatially targeted policies are preferred. In this effort to improve the environmental precision of the farm spatial microsimulation model, Irish pastoral-based livestock systems will be used as a case study. Ireland's agriculture is predominantly grass-based, and its pastoral livestock systems heavily depend on favorable grass growth and crop yield, albeit with varying soils and weather conditions across the country. Additionally, providing a decision support tool with output and cost information based on localized microsimulation models would encourage farmer participation in financial planning.

The thesis employs Ireland (Republic of Ireland) as a case study because the main farm systems are pastoral-based livestock systems heavily reliant on the land base. Under such conditions, the local environment and agronomy play crucial roles, particularly in output and productivity compared to indoor systems where feed is purchased. There is significant spatial heterogeneity in Irish agriculture, with soils, weather, and other agronomic conditions varying across space, influencing yields and agricultural outcomes. The research will improve the quality of data in Ireland concerning farm-level productivity analysis.

Relatively 'good' land in Ireland is concentrated in the South and East, while poorer land is in the North and West of the country (Frawley and Commins, 1996). The most profitable sub-sectors within agriculture, dairy, and to some extent, tillage farming, are predominantly concentrated in the South and East, whereas lower-margin beef and sheep sectors are mainly located in the Midlands, North, and West of the country (O’Donoghue et al., 2014).

Furthermore, the word of the thesis argues for a relationship between behavioral drivers, economic returns, and the spatial dimension of lime nutrient management practices. It aims to fill the literature gap by exploring the relationship between these elements and how they impact each other. Firstly, the research will investigate whether behavioral factors influence farmers' intention to apply recommended lime. Secondly, it will estimate if there is a correlation between farmers' intention to apply lime and farm-related characteristics, such as output, cost, temperature, and rainfall. Thirdly, the thesis will extend and analyze the cost and benefit of liming and demonstrate the spatial dimension of economic return from liming. Finally, it will examine the hypothesis of whether the regions most in need of lime are the regions with comparatively higher farmers' intention to lime.

To conclude the monograph will seek to explore the relationship between investments in key agricultural assets such as machinery, livestock, and buildings and their impact on both the output and costs associated with farming operations. It aims to quantify the extent to which these investments affect productivity and expenses within the agricultural sector. Also, it tried to address the influence of localized natural resources and environmental factors on the spatial distribution of farm income. It investigates to understand how the availability and quality of natural capital, such as soil fertility, and biodiversity, shape the distribution patterns of income across different geographical areas within the agricultural landscape. Additionally, the thesis explores the complex interactions between behavioral patterns of farmers, spatial characteristics of farming landscapes, and income variables concerning nutrient management planning on farms. Finally, it focuses on the development and implementation of decision support tools aimed at enhancing farmers' involvement in financial planning for their agricultural operations. It seeks to identify the key parameters and features necessary for such tools to effectively engage farmers and assist them in making informed decisions regarding financial management within their farms.

1.3. Thesis structure

This thesis comprises eight chapters. Chapter two of the thesis (Theoretical Framework and Literature Review) serves as the foundational pillar upon which subsequent chapters build, by exploring theoretical concepts and reviewing existing literature pertinent to the study of agriculture in Ireland. The section of "Spatial Agronomic and Environmental Drivers," elucidates the factors that influence agricultural practices based on local environmental conditions. This section delves into how aspects such as soil type, climate variability, and topography shape agronomic decisions, emphasizing the need for tailored approaches to optimize productivity and sustainability across diverse geographical settings.

In the section "Soil Fertility," the chapter critically examines literature on soil health and its profound impact on agricultural productivity. Discussions encompass soil nutrient dynamics, organic matter content, and microbial activities, highlighting their pivotal roles in supporting crop growth and resilience. Understanding soil fertility is pivotal for implementing effective nutrient management strategies aimed at enhancing yield while minimizing environmental degradation.

Section "Advantage of Balancing Soil pH Level," expands upon the benefits of managing soil pH levels for optimizing crop yield and nutrient uptake. It synthesizes empirical findings and theoretical frameworks to underscore the significance of maintaining optimal pH conditions in agricultural soils, thereby illustrating how such practices contribute to sustainable farming practices and economic viability. Moving to the section of "Behavioural Drivers of Nutrient

Management Planning," the chapter explores behavioral theories that influence farmers' decision-making processes in nutrient management. Insights from behavioral economics and psychology illuminate factors such as risk perception, social norms, and attitudes towards adopting innovative agricultural practices. Understanding these behavioral drivers is crucial for designing effective policies and interventions that promote sustainable agricultural practices.

Section "Potential Role of Financial Planning Tool," shifts focus to tools and methodologies aiding financial decision-making in agriculture. It discusses the application of cost-benefit analysis, financial modeling, and risk management strategies in enhancing economic resilience and profitability for agricultural enterprises. This section underscores the integration of financial perspectives with agronomic practices to foster sustainable agricultural development.

In the section of "Structure of Irish Agriculture," the chapter provides an insightful overview of the agricultural landscape in Ireland. It examines factors such as farm size, ownership patterns, regulatory frameworks, and market dynamics shaping agricultural practices and outcomes. This contextualization within the socio-economic and policy framework of Ireland offers valuable insights into the structural challenges and opportunities within the agricultural sector. Finally, the section "Research Questions and Current Research Gap" frames the research questions and identifies gaps in current knowledge. This section delineates the study's objectives and outlines the research agenda aimed at addressing identified gaps through empirical research and theoretical analysis. It provides a roadmap for subsequent chapters, guiding the exploration of key issues in agricultural management and policy.

Chapter three (Methods and Data) details the methodologies and data sources employed in the thesis. It has a section "Spatial Models", which introduces various spatial modeling techniques used to analyze agricultural dynamics across different scales. It discusses how these models utilize spatial patterns and relationships crucial for understanding agricultural systems' complexities. Section "Agronomic Based Income Generation Model" introduces a model linking agronomic factors to income generation, illustrating how agronomic decisions impact economic outcomes in agriculture. This model provides a structured approach to assess the economic implications of agronomic practices on farm profitability.

The section of "Simulation Model of the Irish Local Economy" explores a simulation approach to understand economic impacts within the Irish agricultural context. It employs computational simulations to forecast economic trends and assess policy interventions' potential outcomes, thereby informing strategic decision-making in agricultural policy. In section "Deep Neural Networks", the advanced computational techniques are explained for their application in analyzing complex agricultural datasets. This section discusses how neural networks enhance data analysis capabilities, allowing for deeper insights into agricultural productivity trends and patterns. Section "Farm Survey Data" elaborates on primary data collection methods through farm surveys. It discusses the methodologies employed to gather empirical data directly from farmers, providing insights into their practices, challenges, and perspectives.

The section of "Administrative Data" explores the use of administrative records for analytical purposes. This section highlights the utility of administrative datasets in studying broader trends and patterns within the agricultural sector, complementing empirical findings from primary data sources. The section "Choice of Spatial Unit" justifies the spatial scale chosen for the study. It discusses the rationale behind selecting specific spatial units for analysis, considering factors such as data availability, geographical variability, and analytical objectives.

Chapters four to seven consist of four papers. Chapter four is titled "Local natural capital influences on the geospatial distribution of farm incomes"; chapter five is called "The Marginal Effect of Investment in Machinery, Livestock, and Buildings on Irish Agricultural Output and Costs"; and chapter six, which discusses nutrient management plan, is named "A spatial analysis of farmers' intentions to adopt nutrient management practices – a case study of soil pH management in Ireland". Chapter seven includes a technical paper titled "The Importance of Spatial Disaggregation in Providing Agricultural Market Outlook Advice".

Chapter four (Local natural capital influences on the geospatial distribution of farm incomes) investigates how natural capital affects farm income distribution. Its introduction section sets the context by outlining the significance of natural capital and its implications for income disparities in agriculture. It underscores the need to understand how natural resources influence economic outcomes across different spatial contexts.

Its theoretical framework section establishes the theoretical basis for analyzing natural capital's impact on farm incomes. It synthesizes existing literature and theoretical perspectives to develop a framework that elucidates the mechanisms through which natural capital influences agricultural productivity and economic performance. The “Methods and Data" section provides a detailed exposition of the methodologies and datasets employed in the study. It outlines the specific methods used to quantify natural capital indicators and analyzes their spatial distribution relative to farm incomes. The section "Results" presents empirical findings on how natural capital influences farm incomes spatially. It discusses spatial patterns and correlations between natural capital indicators and farm income distribution, providing insights into the factors driving economic disparities within agricultural landscapes.

Finally, its section of "Discussion and Conclusion" analyzes the results and draws conclusions based on the findings. It interprets the implications of natural capital influences on farm incomes, discussing policy implications and potential strategies to enhance economic equity and sustainability in agriculture.

Chapter five (The Marginal Effect of Investment in Machinery, Livestock, and Buildings on Irish Agricultural Output and Costs) of the thesis examines the economic impacts of investments in agricultural assets. Its introduction section introduces the study on investment effects and outlines its significance for understanding agricultural productivity and profitability. The section of "Methodology and Data" outlines the methodologies and data sources used to analyze investment impacts. It discusses econometric models and statistical techniques employed to assess the marginal effects of investments in machinery, livestock, and buildings on agricultural output and costs. Its section "Results" presents empirical findings on the economic effects of investments in agricultural assets. It quantifies the marginal impacts of investments on farm productivity, profitability, and cost structures, providing empirical evidence to inform investment decisions in agriculture.

The discussion section examines the implications of the results for agricultural practices and policy. It discusses how investment decisions influence farm management strategies, technology adoption, and overall economic performance in agriculture. And finally, the section of "Conclusion" summarizes the key findings and their implications for agricultural policy and practice. It synthesizes the empirical evidence and discusses the broader implications of investment decisions on farm sustainability, economic resilience, and competitiveness.

Chapter six (A spatial analysis of farmers’ intentions to adopt nutrient management practices) focuses on spatial factors influencing farmers' adoption of nutrient management practices. Its introduction section introduces the study on farmers' intentions regarding nutrient management and outlines its significance for enhancing agricultural sustainability and environmental stewardship. Its theoretical framework discusses theoretical underpinnings guiding the analysis of farmers' adoption behaviors. It synthesizes behavioral theories and decision-making frameworks to understand the factors influencing farmers' intentions to adopt nutrient management practices. Its "Data and Methodology" section describes the data sources and methodologies used for spatial analysis. It outlines spatial modeling techniques and survey methodologies employed to assess spatial patterns of adoption intentions among farmers.

The results section presents findings on spatial patterns of farmers' intentions to adopt nutrient management practices. It analyzes geographical variations in adoption behaviors, identifying spatial factors influencing adoption rates and strategies. And the conclusion part summarizes conclusions drawn from the spatial analysis of farmers' adoption intentions. It discusses implications for policy interventions, extension services, and educational programs aimed at promoting sustainable nutrient management practices in agriculture.

Chapter seven (The Importance of Spatial Disaggregation in Providing Agricultural Market Outlook Advice) explores spatial disaggregation in agricultural market outlook. The introduction part provides information on the significance of spatial analysis in enhancing market outlook and decision-making in agriculture. Its theoretical framework reviews relevant literature and theoretical frameworks on spatial disaggregation. It discusses methodologies and analytical approaches used to disaggregate agricultural market data and assess spatial variations in market dynamics. The methodology and data section of the chapter details methodologies and data sources used for spatial disaggregation. It discusses geospatial analysis techniques, remote sensing applications, and data mining methodologies employed to enhance agricultural market insights.

Its results part presents findings on agricultural market outlook based on spatial analysis. It analyzes spatial variations in market trends, price dynamics, supply chains, and consumer preferences, providing insights into spatially differentiated market opportunities and risks. The discussion and conclusions section analyzes findings and draws conclusions for market advice and decision-making in agriculture. It discusses implications for market forecasting, risk management, and strategic planning, emphasizing the role of spatial analysis in enhancing agricultural market efficiency and competitiveness.

Finally, the last chapter, chapter eight, concludes and discusses the four papers. This chapter also recommends relevant policy implications and puts forward a potential direction of related future research.

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2. CHAPTER TWO: Theoretical Framework and Literature Review

This chapter consists of six sections, providing important background theory and critical assessment of the relevant studies for the thesis.

2.1. Spatial Agronomic and Environmental Drivers

To grasp the effect of varying agricultural and environmental conditions and grass growth across the country, it is vital to associate them with farm systems, farm size, and animal populations. As components of the biosphere are interconnected and influence each other, understanding the potential causes and the extent of impact of explanatory factors is crucial to this analysis. Land has a significant influence on stocking density, as access to more grazing land allows for the maintenance of a larger number of livestock. Improvements in yield (output per livestock unit) are primarily achieved through the use of genetic technology, as superior genomes result in better output. Furthermore, land with better environmental properties is more productive than land with natural constraints. Agricultural policies, such as subsidies for less favoured areas, also impact farm output and costs.

Agriculture as a whole, including arable and pastoral farming, depends upon spatial environmental conditions such as weather, soil, altitude and temperature. In livestock farming, agronomic factors define the quality and quantity of pasture, which impacts on farm income and costs (Khairo et al, 2008). In the literature, the productivity of arable crops is explained as a function of temperature, irrigation and characteristics of the crop (Spitters et al, 1989). These primary agronomic factors influencing farm earnings are discussed further in the following sub-sections. In the thesis chapters, agronomic variables are referred to soil types, soil principal and physiological characteristics, while temperature, rainfall, continentality and distance to sea are considered as environmental variables.

Soil type and composition will have vital influence on crop yield, i.e. soil nutrients and soil fertility are important catalysts of agricultural profit. On average, soils are composed of about 45 % mineral fragments, 20-30 % soil gas or soil air, 20-30 % water and about 5 % organics or organic matters, while the primary soil particles are sands, silts and clays. Soil classifications vary across countries (Tabor, 1997), for instance in Ireland, great soil groups are classified as podzols, brown podzolics, peat soils and so on (Creamer et al, 2016), while temperature and rainfall interact with soil and influence land grass output (too high/low temperature and too much/little rainfall having negative effect). The main nutrients necessary for crop growth are nitrogen (N), phosphorus (P) and potassium (K), which are taken up by plants (by soil mineralization or decomposition), from chemical fertilizers and organic manures[1], or through fixation from the atmosphere (FAO, 1985). Different plants require specific optimal levels of nutrients.

2.2. Review of Natural Capital

The natural capital includes many factors that are considered as the natural resource of a land or a given environment, and some examples are biodiversity, land use, climate variability, atmospheric composition, and ecosystem services (Costanza et al., 1997; Smith et al., 2017). For instance, ecosystem services are the services that include pollination, pest control, nutrient cycling, and water regulation, which are provided by natural systems and contribute directly or indirectly to farm income. Another example of the natural capital is the changes in atmospheric composition,

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[1] Organic manure is animal waste and can be either liquid slurry, which is in tanks or solid farmyard manure (FYM)

such as increased carbon dioxide levels, which may have complex effects on plant growth and nutrient uptake. However, the thesis mainly focuses on variables like rainfall, temperature, and soil quality in influencing farm output and costs. The reason is that these variables are the main measurable factors that one can relate to farm costs and output. The choice of these variables is also based on the expert advice of farm researchers based in Ireland.

Natural capital encompasses the stocks of natural assets, such as soil, water, air, biodiversity, and landscapes, that provide benefits to humans, termed ecosystem services. Rainfall and temperature are fundamental climatic variables that directly affect agricultural production (Kang et al., 2009; Kukal and Irmak, 2018). Studies consistently demonstrate their critical roles in determining crop growth, pest and disease incidence, water availability, and overall farm productivity. For instance, adequate rainfall and optimal temperature regimes are essential for crop development stages such as germination, and flowering. These relationships can be supported by literature from agricultural sciences and climatology, which highlight the direct impacts of these variables on agricultural outcomes.

Soil quality, encompassing factors like nutrient content, pH, organic matter, and texture, is equally vital. Healthy soils are essential for nutrient uptake by plants, water retention, and root development. The literature extensively documents how soil quality influences crop yields and farm income (Karlen et al., 2001; Selim, 2020). For example, degraded soils with poor structure and nutrient deficiencies often lead to lower yields and increased input costs. The rationale for selecting these variables should be grounded in studies that link specific soil parameters to agricultural productivity, such as research on soil fertility management practices and their economic implications.

Explaining the mechanisms through which these chosen variables influence farm income requires a nuanced understanding of agricultural systems. For rainfall and temperature, the mechanisms are clear: they directly affect water availability, crop growth rates, and the incidence of pests and diseases. Changes in temperature patterns can also impact the timing of planting and harvesting, affecting overall yields and market prices. Soil quality influences farm income through its effects on nutrient availability, crop health, and resilience to environmental stresses like drought or flooding. Mechanisms can be supported by empirical studies that quantify these relationships across different agricultural contexts, providing a robust basis for understanding their economic impacts.

Moreover, the interdisciplinary nature of ecosystem services research emphasizes how natural capital variables interact to provide multiple benefits to agricultural systems. For example, healthy soils not only support crop growth but also contribute to water filtration and carbon sequestration, providing additional ecosystem services that enhance farm resilience and sustainability. These broader ecological interactions should be integrated into the rationale for selecting variables, demonstrating their interconnectedness and cumulative impacts on farm income.

In discussing the choice of variables, it is essential to acknowledge potential limitations or alternative perspectives for the thesis. For instance, while rainfall and temperature are primary climatic factors, local variations in microclimates or extreme weather events may necessitate nuanced analyses. Soil quality assessments should consider regional differences in soil types and management practices that influence agricultural outcomes. By addressing these nuances, the thesis could strengthen its analytical framework and provide a more comprehensive understanding of how natural capital variables shape agricultural productivity. However, because of the lack of available data, the thesis will not take into account other natural capital factors that may impact farm output and costs.

2.3. Soil Fertility

Indoor and outdoor farming systems exist, with indoor systems relying on purchased animal feed such as concentrates and hay. Poor environmental conditions, such as extreme temperatures and precipitation levels, hinder sufficient grass growth output from farmland, forcing farmers to buy animal feedstuff. In contrast, outdoor systems primarily feed their livestock with grass from their farmlands. Regions with relatively balanced environmental conditions, like a balanced temperature and rainfall, are common in outdoor systems, with the Republic of Ireland serving as an example.

Therefore, for the outdoor farming systems grass growth and grass output productivity is the important factor. In order to have a productive grass output from their farmlands, farmers need to maintain a fertile soil. A fertile soil is referred to soil which mainly has an adequate amount/level of pH and macronutrients, such as nitrogen, phosphorus and potassium. Farmers are advised to test their soil fertility and adjust their lime and macronutrients according to the optimal, advised level. For example, Teagasc – the Agriculture and Food Development Authority of Ireland advices farmers to keep their pH level within the optimal range of 6.3 to 7.0 (Wall and Plunkett, 2020).

After applying the macronutrients, they are absorbed by the grass and utilised to grow. However, when the soil pH level lacks to be within the optimal range, macronutrients are not absorbed efficiently and the excess/unabsorbed amount is washed out over time (The Fertilizer Association of Ireland, 2016; Wall and Plunkett, 2016). The inadequate pH level causes the macronutrients to be wasted, which is an economic loss and washed-out chemical fertilisers/macronutrients pollute the environmental.

In order macronutrients to be taken by grass more efficiently, farmers are advised to keep their farmland pH level at the optimal level. One of the widely used way to stabilise soil pH level is to apply lime/limestone ($CaCO3$). Lime serves acts as a pH level conditioner (Wall and Plunkett, 2016) which balances/stabilises soil pH level. Generally, when farmers take the soil fertility test their farmland soil pH level is measured and they are given an advice of how much lime they should apply per a given area and how frequently.

2.4. Advantage of Balancing Soil pH Level

When farmers decide whether to apply lime or not, they weigh the benefits against the costs. If the benefits of liming are greater than the expenses, it encourages them to adopt lime nutrient management planning. This thesis calculates the economic return from liming by estimating the spatial distribution of costs and benefits. The spatial aspect of lime economics assists farmers, farm advisors, and policymakers in formulating and evaluating their planning, advice, and policies more effectively.

In the thesis's chapter six, the profit function is defined as net benefit of applying lime, which is total benefit of lime application less total cost of liming:

$$NB_{i,j} = TB_{i,j} - TC_{i,j}$$

where $NB_{i,j}$ refers to net benefit of applying lime per farm (i) and per hectare (j) or per livestock unit (j). $TB_{i,j}$ is total benefit of liming and $TC_{i,j}$ is total cost of it. In the results section, the estimation of net benefit of applying lime will be given per hectare and per livestock unit, so that there is no bias with the respect to farm area and farm animal size.

The total benefit of lime application represents the total saved fertilizers/macronutrients' monetary amount (€), which is a wasted monetary amount of fertilizers given farmlands suboptimal pH level. In other words, the lower/suboptimal soil pH level a farm has, the higher the amount of fertilizers/macronutrients will be wasted (because of low fertilizer absorption rate by plants), and this wasted amount is considered as the total benefit if the farm had the optimal pH level. So, if a farm soil pH level is within the range of the optimal pH level, then the total economic benefit of liming for this farm will be 0 (nothing), as it will be assumed that no amount of fertilizers will be wasted, conditional upon farmers following the recommended nutrient management advices and applying only the needed quantity of macronutrients.

The total cost of lime application that is discussed in the thesis is estimated as the total cost of needed lime and application of it to bring a given farmland soil pH level from below the optimal level to the optimal range. For instance, a farm with a suboptimal pH level of 3.0 will be having a higher total cost of lime application compared with another farm with a below optimal level of 4.0. Same as the net benefit of applying lime, in the results section, the total cost of lime application will be given per hectare and per livestock unit. The cost of liming includes the cost of lime itself and its spreading fee. In Ireland, as of 2018, generally used ground limestone (calcium carbonate) costs on average €25 per tonne, which includes both the cost of lime and spreading fee (The Fertilizer Association of Ireland, 2016).

2.5. Behavioural Drivers of Nutrient Management Planning

In terms of nutrient management strategies, farmers are impacted by their beliefs and psychological tendencies (Daxini et al., 2018). The psychological behavior of farmers will affect their decision to follow lime management recommendations, and if their intention towards applying lime is negative, they may choose not to lime their farmland even if necessary. To examine the behavioral aspect of lime nutrient management practices, this study must utilize a theoretical framework from behavioral psychology.

In the literature of behavioral psychology, there are several theoretical frameworks related to behavior and beliefs. One of them is the Theory of Reasoned Action (Fischbein and Ajzen, 1975), which explains the relationship between behaviors and attitudes. However, this theory has been criticized for not accounting for certain situations that are not available to certain individuals, which, according to this theory, should be influencing individuals' intentions (Eagly and Chaiken, 1993).

Another theoretical framework in the behavioral field is the Fogg Behavior Model (Fogg, 2009). This model states that individual behavior is determined by ability, motivation, and triggers. Psychological conditions, such as pleasure, pain, and hope, are part of motivation, while time, money, and physical effort are included in the ability part of the model. The author claims that triggers serve as reminders for individuals' behavior, with examples such as text messages and alarms. Although this theoretical model can be used by psychological practitioners to achieve certain behavioral goals for their subjects, it lacks a broader scope of influential factors of behavioral intention, such as group/customary norms and behavioral attitudes.

The Theory of Planned Behavior is another theoretical framework from behavioral psychology that aims to evaluate factors influencing behavioral intention (Ajzen, 1985; Ajzen, 1991). The components/pillars of this theory are attitudes, subjective norms, and perceived behavioral controls (Ajzen, 1991; Madden et al., 1992). These components, in turn, influence behavioral intention, which leads a subject to actually carry out/perform a given action/task. The formula for this theory is as follows (Ajzen, 1991):

$$BI_i = w_A A_i + w_{SN} SN_i + w_{PBC} PBC_i$$

where BI_i represents behavioural intention, A_i attitudes, SN_i subjective norms and PBC_i perceived behavioural controls. w_A, w_{SN} and w_{PBC} are the statistical coefficients or weights.

Each influencing components or predictors of behavioural intention refers to different psychological contents. The attitudes explain the favourable or unfavourable evaluation level of a given behaviour or action. The subjective norms refer to beliefs regarding approval or disapproval of a certain behaviour or action by majority in a given region. The perceived behavioural controls define level of difficulty or easiness of performing/executing an action or behaviour by a subject. The reasons to use this theoretical framework as the thesis's behavioural framework are the follows. This theoretical framework has been researched and used widely. It encompasses broader and clear-cut elements of beliefs and behaviours. Additionally, it fits well in the context of lime application recommendations and it has been already deployed by Daxini et al. (2018) to access behavioural intention of nutrient management practices.

2.6. Potential Role of Financial Planning Tool

The agricultural market environment's intricacy, marked by greater volatility, intricate investment situations, and sustainability concerns (O'Donoghue et al., 2016), has underscored the significance of farmers' participation in financial management. Improved financial management is essential across all profitability levels. However, farmers are more likely to embrace agricultural technologies and practices than financial strategies (Hennessy and Heanue, 2012). This tendency emphasizes the need for more extensive planning to strengthen resilience in a challenging farming environment. Furthermore, it has been discovered that decision support tools can improve stakeholder engagement and reduce conflicts (Mukhtar and Bahormoz, 2022).

Despite the availability of tools like the eProfit Monitor (ePM) decision support system (Morrow et al., 2004) to aid in financial management and planning, their adoption has been limited. Although the use of the eProfit Monitor has grown significantly, with about 10,000 farmers employing it, this number still only represents a small percentage of the overall farmer population. As discussed by many scholars, big data monitoring support systems and digital transformation (Javorník and Husák, 2022) would also help agricultural participants to take advantage of these systems/tools.

The foundational element of the farm financial information system is its biophysical methodological framework. Weather is a primary time-variant agronomic factor influencing grass growth. To comprehend grass growth drivers, it's essential to gather weather and soil data at specific grid points, aligning with remote sensing-based grass growth measurements. Analyzing the effects of varying agronomic conditions and grass growth nationwide requires integrating this data with farm data, management decisions, and outcomes. This integration is then connected to market prices to model the market effects resulting from the interplay of these biophysical elements. For instance, Rao et al. (2016) analyze the milk market and its linkage to the household income within dairy hubs. Additionally, financial decision support tools can better navigate through farm investment cycles, and in turn reduce costs, and increase the profit (Haydarov and Zhang, 2023).

We utilize spatial microsimulation methods to create a base dataset, building upon methods developed in the creation of the Teagasc Simulation Model of the Irish Local Economy (SMILE). Later in the modelling process, we analyse the output and cost impact at both localized and farm levels for individual farms across the country by associating farm information with spatial dimensions. To achieve this, we utilize biological and economic data from farm systems, including animal demographics, feed supply and demand, imported feed, other costs, and animal outputs. This analysis involves integrating spatially referenced farm and biophysical data to generate farm-level output and cost results.

This thesis's chapter seven focuses on the development of a Decision Support Tool to provide localized advice. The Decision Support Tool will include benchmark information, such as top, middle, and bottom in terms of farm market gross outlook, farm overhead costs, farm direct costs, and net farm profit. The Decision Support Tool provides benchmark information at the farm level, per unit of utilized agricultural area, and livestock unit. Additionally, this tool gives the most recent situation information of the agricultural sector by extracting data from the Irish Central Statistics Office.

The Predictive Decision Support Tool in this thesis incorporates key elements of financial statements, specifically farm market gross output, farm overhead costs, farm direct costs, and net farm profit. The base for this framework is outlined by Haydarov et al. (2024). These variables will serve as the basis for providing benchmark information at the farm level, per utilized agricultural area, and per livestock unit. Net farm profit, profit margin, or gross margin is defined as follows:

$$P_{net} = O_{market} - C_{direct} - C_{overhead}$$

O_{market} represents farm gross market output, which is total sales less purchase of livestock and crops. C_{direct} is total farm direct costs that are directly incurred by farm enterprises and can be allocated for each farm systems, while $C_{overhead}$ is total farm overhead/fixed costs which cannot be traced by a specific farm enterprise and recorded as costs incurred by a farm rather than a specific system.

The benchmark report information is categorized into top, middle, and bottom tiers, with each representing one-third of either farm output or costs. Alongside farm-level benchmark details, the Decision Support Tool provides information per utilized agricultural area. This includes market gross output, farm overhead and direct costs, and net farm profit, all divided by the farm's utilized agricultural area in hectares. Similarly, the benchmark per livestock unit is determined by dividing net farm profit, total farm gross output, and total direct and overhead costs by the farm's livestock unit. Although other farm-related information could also be provided to further enhance the predictive tool, such as return on farm investments (Haydarov and Zhang, 2023), these details are very farm-specific, and modelling them with minimum input information from farmers is challenging.

2.7. Structure of Irish Agriculture

Irish agriculture operates within a pastoral grass-based system due to its Oceanic climate (Peel et al., 2007) and the Atlantic Central (ATC) environment zone, characterized by a temperate, warm, and balanced climate with consistent rainfall throughout the year (Metzger et al., 2005). The favorable climatic conditions in Ireland have led to the predominance of outdoor pastoral farming systems such as beef cattle rearing, dairy farming, and sheep farming for meat production.

The agricultural land area of the Republic of Ireland (ROI) spans 4.4 million hectares (ha). Forested land covers 0.73 million ha, with the total land area of the country amounting to 6.9 million ha (Agricultural Science Association (ASA), 2018). Pasture, silage, and hay occupy 3.6 million ha of agricultural land, while livestock grazing utilizes 0.5 million ha, and less than 0.36 million ha is allocated for crops, horticulture, and fruit cultivation (ASA, 2018).

The primary commodities of the Irish agricultural sector in terms of goods output include milk, cattle, pigs, and sheep, with their respective shares (excluding forage) in 2016 being 36.1%, 35.1%, 7.5%, and 3.8%, respectively (DAFM, 2018). The key inputs or intermediate consumption expenditures in agriculture consist of animal feed, forage plants, fertilizers, maintenance and repair, with their shares in the same year being 27%, 21%, 10%, and 9%, respectively (DAFM, 2017).

The Irish soil map (Figure 1) illustrates the significant variation in soil types across the country. This diversity highlights the importance of considering localized spatial characteristics when simulating from survey data to control totals, as failing to account for these factors can introduce biases that affect the accuracy of the model. For instance, placing a farm from the survey with podzolic soil type into a region of control totals with gleys soil can result in inaccuracies in the results. This variability provides natural advantages to some farmers in terms of farm output, while others may face disadvantages due to physical constraints.

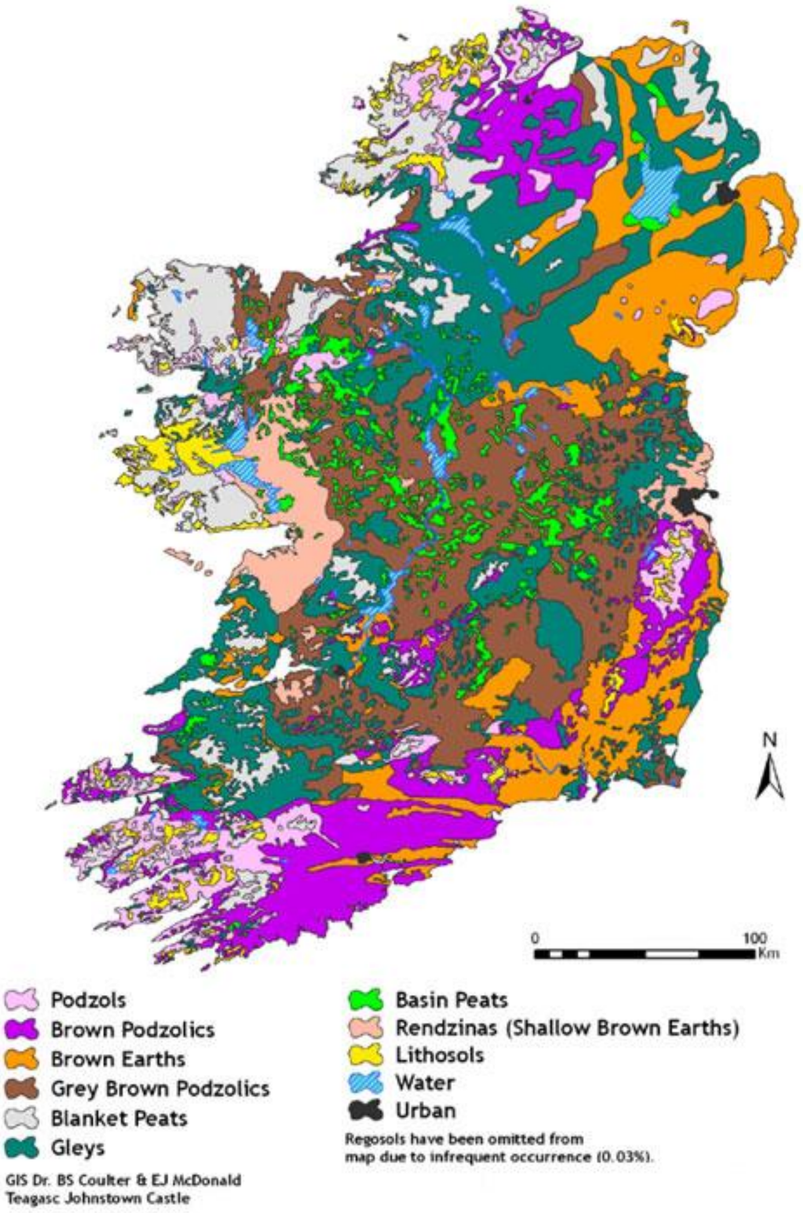

Figure 2.1. National Soil Map of Ireland (Source: Teagasc, no date)

2.8. Research questions and current research gap

The thesis will try to address the following four main research questions in chapters four to seven:

1) Does localized natural capital play role in explaining the spatial distribution of farm income?

2) Can investment in machinery, livestock, and buildings influence agricultural output, and costs, and by how much?

3) What are interactional dynamics of behavioral, spatial, and income variables on farm nutrient management planning, and soil pH level as a case study?

4) How can a farm decision support tool and which parameters help increase farmers' engagement with farm financial planning, and how can this be pursued and achieved?

To summarize, the thesis tries fill the following research gap. It addresses the question of whether localized natural resources, such as soil quality, water availability, and climate conditions, impact the spatial distribution of farm income, and how the environment influences agricultural productivity and financial outcomes. Secondly, it examines the effects of capital investments (e.g., machinery, livestock, infrastructure) on agricultural output and costs. By quantifying these impacts, we can better understand the trade-offs associated with different investment decisions.

Thirdly, the thesis contributes to the literature by investigating the complex interplay between behavioral factors (such as farmer decision-making), spatial variables (such as land use patterns), and farm income levels. The focus is on how these factors jointly influence nutrient management planning and soil pH levels on farms. Finally, the study will address the development and implementation of decision support tools for farmers, and aims to identify parameters that enhance farmers' engagement with financial planning. By understanding these parameters, we can promote sustainable practices and improve overall farm management.

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3. CHAPTER THREE: Methods and Data

This chapter explains the main methodological and data choices. Chapters four to eight delve into specific methodological techniques and datasets utilized for a given thesis chapter. The primary methodological choice is the microsimulation technique, while the main dataset supporting the findings is Teagasc's National Farm Survey data, which are discussed in this chapter.

3.1. Spatial Models

The approach of thesis regarding spatial microsimulation modelling involves extracting data from a survey to match control or census totals. These totals do not account for spatial variations in attributes. Current spatial microsimulation models at the farm level employ sampling or reweighting methods to generate a synthetic spatial farm dataset, but they do not fully integrate geographically diverse agronomic variables. The drawback of sampling without considering local environmental conditions is that the results may not be precise across different environmental settings. Hence, a solution is required to address this issue by capturing the spatial diversity of agronomic factors.

The sampling methods for spatial farm-level microsimulation models may involve sampling or weighting farms from one particular agronomic condition and making them representative of another agronomic circumstance. For instance, one farm from a national distribution can be sampled to represent a local distribution. The issue arising in this case is that representative sampling may not be adjusted for local environmental contexts; thus, the weighting by farm system, size, and type may not accurately represent the same environmental conditions.

A common weakness of existing spatial models is that the local context of variables that change depending on physical location is not adequately incorporated, as seen in the models of Ballas et al. (2007), van Leeuwen and Dekkers (2013), Hynes et al. (2009), and Ramilan et al. (2012). In the methodology described in chapter four, the income generation model will need to be adjusted, and the localized agronomic heterogeneity of the spatial microsimulation model will need to be improved. Therefore, the contribution of this chapter will involve considering the local agronomic context to enhance the environmental accuracy of the farm-level spatial microsimulation model, thereby increasing the local accuracy of farm profit measurement.

3.2. Agronomic Based Income Generation Model

Initial studies on income generation models focused on wage comparison and distribution (Blinder, 1973; Oaxaca, 1973). Bargain and Callan (2010) adopted a tax-benefit microsimulation model using a decomposition approach to assess the true value of evaluating policy changes alongside other structural reforms. Bourguignon et al. (2001) employed microsimulation-based decomposition techniques to examine income distribution in Taiwan. O'Donoghue et al. (2017) utilized a Parametric Income Generation Model similar to Bourguignon et al. (2001) and integrated a tax-benefit microsimulation method with price adjustments, incorporating explanatory variables such as time, weather, education, and environmental characteristics into the model. However, there are relatively few agronomic based income generation models that have spatial dimension, and consider natural capital of farmlands. This is another motivating point that encouraged to use this technique in the thesis, which is comparatively underutilized.

3.3. Simulation Model of the Irish Local Economy

The Simulation Model of the Irish Local Economy (SMILE) developed by O'Donoghue et al. (2017) will serve as the experimental platform for the methodology outlined in this study. The primary objective of the SMILE framework is to assess the socio-economic impacts of economic and policy modifications. The model aims to evaluate the effects of these alterations within the realms of agricultural, rural, and environmental policies, in addition to the conventional analysis of economic and social policy adjustments. O’Donoghue et al. (2013) details the construction and calibration of the SMILE model, while O’Donoghue et al. (2017) elaborates on the recent advancements in the SMILE model and elucidates the process of generating a foundational population using Census of Agriculture data and assigning specific attributes to each farm in the dataset through spatial microsimulation techniques.

The SMILE model has been widely utilized for various purposes including simulating income distributions (Morrissey and O’Donoghue, 2011; O’Donoghue et al., 2013), estimating variations in farm income (Haydarov et al., 2024), conducting network analysis of forests (Cullinan et al., 2008), modeling spatial farm income (Hynes et al., 2009). In our sampling methodology, several factors must be considered such as the spatial heterogeneity of livestock, avoiding issues related to income smoothing during sampling, and ensuring computational efficiency in terms of time and cost (O’Donoghue et al., 2017).

The Quota Sampling (QS) method, developed by Farrell et al. (2013), is chosen a choice of the thesis for its ability to address these factors and is deemed the most suitable methodological framework for extending the SMILE model. QS is a probabilistic reweighing technique that adjusts survey data based on specified constraint totals for individual predefined small areas. During the sampling process, the initial step involves identifying matching variables between micro unit surveys and small area datasets. These 'match' constraint variables should share the same unit, such as individual, household, farm, or small area level Electoral Division (ED). Unconstrained variables along with target variables can then be linked to these matching variables. The subsequent step entails defining the small area calibration totals, which will serve as benchmarks, often referred to as 'quotas' (Farrell et al., 2013).

3.4. Deep Neural Networks

Deep Neural Networks consist of artificial neural networks with multiple hidden layers. These networks comprise an input layer with neurons representing predictive or explanatory variables (Larochelle et al., 2009; Montavon et al., 2018; Sun et al., 2018). Neurons in the hidden layers compute values by summing the products of previous neurons (or input values) and their corresponding weights. The output layer, serving as the final layer, also computes values based on preceding neurons and their weights. The neural networks of the chapter five of the thesis will have four hidden layers, each with five neurons; the input layer features three neurons (representing investment in machinery, livestock, and building), while the output layer contains one neuron (representing farm gross output, direct costs, or overhead costs). However, the number of hidden layers and neurons in the input, hidden, and output layers can vary based on the specific architecture of the deep neural network. In this thesis, the deep neural networks are structured with four hidden layers, each comprising ten neurons.

Initially, all weights are randomly assigned, leading to predicted outputs that may deviate significantly from actual values. To minimize errors associated with weights in deep neural networks, backpropagation is employed. This technique helps reduce errors and fine-tune weights during each prediction iteration, aiming to decrease errors progressively and enhance the accuracy of predicted values.

3.5. Farm Survey Data

In this thesis, the research is centered on Ireland, chosen for its predominantly pastoral-based agricultural system within the EU. The primary data source utilized is the Teagasc National Farm Survey (NFS), a component of the Farm Accountancy Data Network (FADN). The NFS provides comprehensive farm-level characteristics essential for conducting microeconomic analyses. Initiated in 1972, the NFS is an annual publication derived from face-to-face interviews conducted voluntarily by a professional data collection team with approximately 1,000-1,200 farms participating each year. The survey spans an average of six years per farm and represents a significant portion of farm output in Ireland, excluding very small operations and specific enterprises like pig, poultry, or horticultural operations. The sample is regularly updated to account for farms exiting the survey for various reasons and aims to assess financial aspects such as gross output, costs, income, investment, and indebtedness across diverse farm systems and sizes.

For the microsimulation model's development, a micro dataset of farms with relevant variables is essential, requiring georeferencing to incorporate spatial variables as highlighted earlier. Therefore, the primary data source remains the Teagasc National Farm Survey (NFS), which is georeferenced and linked to environmental variables from administrative datasets like census data. Annually, around 1,000 farms are randomly selected and weighted to ensure national representation for the Republic of Ireland. This voluntary survey excludes pig and poultry systems and serves various purposes including policy formulation, research, financial analysis, and performance evaluation within the EU's FADN framework.

The NFS gathers key variables such as costs, subsidies, purchases, assets, liabilities, yields, inventories, and sales through electronic recording by Teagasc research technicians. Farms in the survey are categorized into dairy, cattle rearing, cattle other, sheep, and tillage systems; however, poultry and pig systems are not represented due to their limited numbers. A limitation of using NFS data is the insufficient representation of small farms and those with lands designated for silage or leasing without animals. To address these limitations, adjustments will be made to align small farm sizes with existing agricultural systems databases and exclude non-animal-holding farms from census quotas while incorporating leasing income into the target variable of gross output.

3.6. Administrative Data

The Animal Identification and Movement (AIM) System serves as a central database provided by the Department of Agriculture, Food, and the Marine (DAFM), tracking animal movements from birth to slaughter between herds. The AIM system database contains detailed information such as calf births categorized by month, gender, sire type, and the number of beef and dairy calves. Additionally, data on mart movements by month, gender, breed, and farm-to-farm movements are recorded in the AIM system. DAFM also includes details on cattle disposals and herd age profiles in the AIM System, with annual publications available (DAFM, 2017).

Within the AIM system, farm types are classified into categories like specialist beef production, specialist dairy, specialist sheep, mixed grazing livestock, specialist tillage, among others. The primary economic size systems identified are specialist dairy, specialist tillage, and 'other' farm types.

Land use and area information are documented in the Land Parcel Information System (LPIS), a national spatial dataset created using aerial photographs and precise satellite images. Each land parcel is assigned a unique identification number for tracking associated attributes. LPIS plays a crucial role in monitoring the European Union's Common Agricultural Policy by verifying eligibility for area-based subsidies. Irish LPIS data includes details like parcel identification numbers, herd numbers, digitized parcel areas, crop descriptions, commonage status, and claimed crop areas (Zimmermann, 2016).

3.7. Choice of Spatial Unit

In terms of the spatial unit selection, this model will be calibrated at the sub-catchment level. The sub-catchment data sourced from DAFM offer insights into 583 sub-catchments distributed across 46 catchments. Given the importance of water quality as a key factor, our analysis will be conducted at the sub-catchment level. The rationale behind this decision stems from the documented inadequacies in Irish water quality, as highlighted in a report by the Environmental Protection Agency (2018). The report indicates that approximately 30% of river channels exhibit substandard quality, with groundwater areas showing contamination rates of 25% and 55% by nitrate and faecal coliforms, respectively. Recent findings from the EPA (2018) attribute agriculture, waste management, and forestry as the primary drivers of water quality deterioration in Ireland.

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4. CHAPTER FOUR: Local natural capital influences on the geospatial distribution of farm incomes

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Abstract

This paper examines the impact of natural capital characteristics such as soil quality, continentality (regional climatic differences) and environmental (rainfall and temperature) on farm market gross margin. The natural capital variables vary geographically and therefore differentially influence farm outputs and costs depending on location. In order to account for the geospatial heterogeneity of natural capital, we use a system of equations known as an income generation model that incorporates physical capital, human capital, and natural capital to adjust the data within the geospatial microsimulation model. In our model, we utilise agricultural administrative and National Farm Survey data. The incorporation of the geospatial heterogeneity due to local variations in natural capital results in considerable adjustments in simulated agricultural incomes across the case study country: Ireland, reflecting agronomic differences arising from the natural capital condition. The results show that after incorporating natural capital drivers into our model, market gross margin per hectare increased in the South and South-East. In contrast, sub-catchment level gross margin per hectare values decreased in the Midlands and parts of the North. Decomposing the variation in income between districts and within districts, we find that accounting for heterogeneity in natural capital also reveals greater income variability, particularly in relation to between-district variability. The outputs of the study demonstrate the impact of natural capital on farm income and the importance of accounting for localised environmental and agronomic conditions.

Key words: Farm level geospatial modelling, microsimulation, geospatial variation, agronomic characteristics

JEL codes: C15, C63, Q10, Q19

4.1. Introduction

Agriculture is a sector that is heavily impacted by public policy both through regulation (food safety, environmental condition) and through subsidies that support food security and environmental public goods. There is therefore extensive use of policy simulation models to understand the impact of policy on the sector (Shrestha et al., 2016; O'Donoghue, 2017b). As a land-based industry, agriculture relies more than most other sectors on the extent and condition of the underlying natural capital, particularly in terms of soil quality and the availability of water. (Emran et al., 2019; Macholdt & Honermeier, 2017). Due to geographical variations in natural capital, 'place' is also an important factor to consider in relation to policy analysis, particularly where subsidies are related to "Areas of Natural Constraint" or for catchment scale modelling (Ramilan et al., 2012). Yet many of the datasets that rely on farm income modelling (Kelly et al., 2018) are either not georeferenced or are not representative at a geospatial scale. While geospatial or spatial microsimulation methods have been developed to undertake policy analyses at a local scale (Hynes et al., 2009b; van Leeuwen and Dekkers, 2013), this paper suggests a method to improve geospatial consistency between underlying natural capital and farm level outcomes, which then helps to understand the impact of natural capital on farm income.

Microsimulation is a simulation or sampling technique that utilises microdata to simulate the impact of policy, economic or social change on micro units such as the individual household, firm or farm (O'Donoghue, 2014). Geospatial microsimulation refers to microsimulation with locational (geospatial) information, which is used for geospatial policy analysis or other location-based studies (Rahman and Harding, 2016; Tanton, 2018; Tanton, 2014). As current farm datasets lack farm survey variables with geospatial/locational information, geospatial microsimulation techniques are used to combine farm survey datasets with national (census) datasets that contain the required geospatial information to produce a geospatial distribution of farms with detailed farm characteristics consistent with the local natural capital or environmental context.

There are many examples of how such models can be used for geospatial policy analysis and for ex-ante farm-level evaluations (of for example, the role of differential agronomic and environmental factors in designing policies such as the EU Green Deal or the Biodiversity Strategy 2030). Shrestha et al. (2007) simulate the geospatial distributional impact of the 2005 Common Agricultural Policy (CAP) reforms, while O'Donoghue (2017b) simulate the impact of the 2014 reforms and Vidyattama & Tanton (2020) simulate the geospatial distributional impact of an external market change on farmer financial distress.

From an environment perspective, Hynes et al., (2008) model habitat conservation and participation in agri-environmental schemes at a local geospatial scale. Hynes et al. (2009a) model the geospatial distribution of greenhouse gas emissions and Chyzheuskaya and O'Donoghue (2017b) and Ramilan et al., (2012) use a geospatial microsimulation modelling framework at catchment scale to simulate the economics of farm level water quality mitigation measures.

Geospatial microsimulation models are generated by either sampling or reweighting survey data to be consistent with a geospatially representative dataset such as a small area census file (Tanton and Vidyattama, 2020). In this way the model combines both farm level contextual information and geospatial characteristics, thus combining the best of both datasets. This raises a number of issues. Typically farms are sampled or reweighted based on demographic information such as farm-size, household-income, age of the farmer as in the case of van Leeuwen and Dekkers, (2013) or milk volume, cow numbers and farm size of Ramilan et al. (2012). Vidyattama and Tanton (2020) also utilise a variety of farm level demographic and economic characteristics such as farm household income, farm type, the value of agricultural operations, age group by sex, household composition and non-school qualifications.

These variables are sufficient for the analysis of demographic off-farm characteristics (van Leeuwen and Dekkers, 2013), however in considering the impact of local natural capital on agricultural productivity or the impact in reverse of agriculture on the condition of the natural capital in the local environment, these models may not adequately reflect local variations in natural capital and consequent variations in farm incomes. If natural capital variables are not used in the weighting or sampling that generates the base data of geospatial microsimulation models, then the outputs and costs will not reflect the local extent and condition of the natural capital. While Hynes et al. (2009a) and O'Donoghue (2017b) utilised a simple six category soil variable to produce farm level microsimulation models, the effective incorporation of natural capital variables is more complex.

Natural Capital as a concept is useful in considering environmental drivers of agricultural outcomes (Helm, 2019). The incorporation of additional natural capital variables during the geospatial microsimulation data creation process is however challenging due to sample size and resulting high weights. In this paper we present an alternative approach to improving the geospatial natural capital resolution in agricultural and ecological policy models, focusing on pasture-based livestock systems which are particularly influenced by heterogeneity in natural capital (environmental and agronomic) and are important drivers of ecosystem condition. In addition to natural capital, there are other factors that could influence farm output and costs, such as managerial capacity and market volatilities, which the paper does not analyse.

In analysing farm level impacts in the context of geospatial farm microsimulation modelling, Ireland provides an example of pastoral livestock systems with varying environmental and agronomic contexts. The major commodities of the Irish agricultural sector are milk, cattle, pigs and sheep with shares (excluding forage) in 2016 of 36.1%, 35.1%, 7.5% and 3.8%, respectively (DAFM, 2018). Livestock production is pasture based with the main inputs (or intermediate consumption of agriculture) in terms of expenditure including animal feed, forage plants, fertilisers, maintenance and/or repair, with shares of 27%, 21%, 10% and 9%, respectively (DAFM, 2017a).

This paper contributes to the literature by building on an existing farm-level microsimulation model SMILE (the Simulation Model for the Irish Local Economy) (O'Donoghue et al., 2012), to incorporate the environmental and agronomic impact of policies at farm level, thereby improving the geospatial reliability of agricultural and ecological modelling. The improved model is then used to investigate the effect of natural capital on farm market gross margin.

4.2. Theoretical Framework

Natural Capital

"Natural capital describes natural assets in their role of providing natural resource inputs and environmental services for economic production... is generally considered to comprise three principal categories: natural resource stocks, land and ecosystems".[2] Natural Capital can be further defined as the stock of natural or ecosystem assets which include geology, soil, air, water and all living things, from which we derive a range of services, often called ecosystem services, such as

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[2] stats.oecd.org/glossary/detail.asp?ID=1730

the food we eat, the water we drink and the plant materials we use for fuel, building materials and medicines, climate regulation and natural flood defences provided by forests, carbon stored by peatlands, or the pollination of crops by insects or cultural ecosystem services.[3] Natural capital is accounted for in terms of the *extent* of elements such as grassland, cropland, forest, heathland, scrub and their *condition* as in the case of soil quality, species accounts, nutrient accounts and related water quality accounts, along with *services* (agriculture, ecosystem) and *benefits* (economic) [4]. In the System of Environmental Economic Accounting, ecosystem assets or stocks are divided into components ecosystem extent and condition.

While many geospatial agricultural and ecological analyses are strong on modelling physical capital and to some degree ecosystem extent (intensive and extensive grasslands, cropland), these models are typically weaker on the ecosystem or natural capital condition. As already highlighted, geospatial microsimulation models are notably weaker in this dimension and as a result, tend to underestimate the geospatial heterogeneity of farm incomes, which are often used for place-based policy analysis. In grass-based livestock farming, the focus of this study, agronomic and environmental characteristics of natural capital define the quality and quantity of pasture growth that is driven by soil and weather, which in turn impacts on farm costs and output (Khairo et al, 2008). In this paper, the agronomic variables used describe soil quality e.g. peat and mineral soils, and physiological characteristics e.g. topography, while environmental variables include temperature, rainfall, continentality[2] and distance to sea.

Environmental and agronomic variables, such as temperature, rainfall and soil are an essential driver of natural capital condition (Dominati et al., 2010). Soil and its mineral

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[3] https://naturalcapitalforum.com/about/

[4] https://ec.europa.eu/environment/nature/capital_accounting/pdf/MAES_INCA_2018_report_FINAL-fpub.pdf

composition is an important part of farm natural capital for grass growth (Dong et al., 2012; Kenny, 2017), influencing grass and crop yields and ultimately farm output (Zhou et al., 2006). In this paper, soil quality accounts for different characteristics such as fertility, soil pH, nutrient properties and physiological properties.

Temperature and rainfall interact with soil to influence grass production. In turn, the physical quality (e.g. trafficability) of farm soil and grass growth-rate largely determine the livestock carrying capacity of land. There is however, wide variation in the distribution of soil quality classes across Ireland (Creamer et al, 2014). This variation confers natural advantages for some farmers with regard to greater farm output, while other farmers are disadvantaged as a result of natural constraints. Table 4.1 provides an example of the heterogeneity of livestock density and feed requirements in the South (SE and SW) compared to the border area in the North. The southern counties have largely well-drained soils compared to the generally wetter soils in the North, allowing for substantially greater carrying capacity in terms of livestock density per hectare on the better soils, as weather differences result in a longer grass-growing season in the South than in the North. Thus, animals can be kept outdoors on grazed grass rather than indoors on more expensive silage or purchased feed. As a result, purchased feed cost per animal is typically lower for farms in the South than in the North.

Table 4.1. Stocking Rate and Purchased Feed Requirements in Different Regions

	Livestock Unit (LU) per Ha			Feed (€) per LU		
Land Area	North/Border	SE	SW	North/Border	SE	SW
< 20 Ha	1.68	2.39	2.22	163.9	97.1	120.1
20-30 Ha	1.70	2.28	2.28	253.5	280.3	345.4
30-50 Ha	1.78	2.13	2.12	347.3	223.5	265.3
>= 50 Ha	1.84	2.10	1.90	339.8	188.6	256.9

Source: Teagasc National Farm Survey 2014
Note: LU per Ha – Stocking rate or livestock units per hectare; Feed (€) per LU - Purchased feed per livestock unit.

Even in a relatively small country like Ireland, ecosystem condition due to agronomic and environmental differences across the country can cause considerable variability in farm output (e.g. lower grass growth and higher fodder costs on less productive soils and/or reduced livestock carrying capacity/livestock density per hectare due to high rainfall).

Measuring farm profitability

Agricultural income is comprised of income from both the market (sales) and from agricultural subsidies (such as the Common Agricultural Policy (CAP)), however this paper focuses only on income which is directly influenced by agronomic and environmental variables, namely market income. In estimating farm market income, it is necessary to understand the interaction between the elements of farm production, i.e. output, costs, agronomic and environmental factors. Geographical location and the associated agronomic and environmental characteristics are key elements influencing farm output and cost, manifested by grass output, which is the main fodder in grass-based livestock systems. The area of land available to the farm and the soil quality (productivity, drainage and topography) influence livestock density and crop yields, however yield is also influenced by genetic factors.

Farm gross margin (farm gross output less total direct costs) is one of the primary measures used to evaluate farm profitability. Farm gross output can be defined as the sum of the product of the price and the volume of output per enterprise i. Total direct costs are all directly traceable costs farm costs. The production technology per farm enterprise is expressed as (Equation 1):

$$V_M^i = A_i K_i^{\alpha} L_i^{\beta} X_i^{v} ha_i^{\delta} lu_i^{\mu} E_i^{\psi} = f_i(A, K, L, X, ha, lu, env/\alpha, \beta, \upsilon, \delta, \mu, \psi) \qquad (1)$$

A_i is Total Factor Productivity (TFP), while K_i, L_i and X_i represent capital, labour and the remaining inputs for given enterprise i, respectively. ha, lu and E express utilised agricultural area (hectare), livestock unit and environmental and agronomic factors, while $\alpha, \beta, \upsilon, \delta, \mu, \psi$ present the output elasticities of A, K, L, X, ha, lu, E, respectively.

There are a variety of reasons for variation in the level of production in the short run. First of all, for a given land base, animals may be purchased or sold, thereby changing the stocking density or the area of land under livestock. Secondly, the yield can vary either in the long-term through breeding, or in the short run through improvements as a result of buying-in animals of improved genetic merit, or variations in feed or fertiliser use. In the short run, it is assumed that land area is fixed, given comparatively low land sales in Ireland, although land may also be accessed through land rental agreements.

The equation in relation to costs is as follows, where W_{CV}^{i} is the price of input costs (both direct and overhead costs) and X_{CV}^{i} represents the volume of inputs (Equation 2):

$$C_v = \sum_i w_{CV}^{i} X_{CV}^{i} \tag{2}$$

We include in this definition of variable cost, overhead costs such as utilities and fuels that vary with production. Another long-run overhead cost associated with, for example, depreciation of assets or interest payable on loans, is also included in overhead costs. On the other hand, direct costs are directly traceable to a particular farm system, such as animal feedstuffs.

While some inputs (such as land) are often thought to be comparatively independent of production within the short run, or assets such as machinery and buildings and to some extent labour, many of the inputs like fertiliser, purchased animal feed, seeds and crop protection are endogenous with production. There is some substitution between inputs so using greater quantities of fertiliser (within limits) in tandem with improved grassland management can reduce the necessity for purchased feed stuff or vice versa.

In this paper, we use the SMILE model to investigate the impact of natural capital variables, focusing on the impact of the natural capital variables on the farm market gross margin. The SMILE model has been used in many peer-reviewed analyses (O'Donoghue et al., 2012, 2013; O'Donoghue, 2017b). The robustness of the model has been demonstrated through testing of simulated results against target variable(s) totals and validated against assumptions. Please refer to the references mentioned earlier for more information.

4.3. Methods and Data

This section describes the development of a modelling framework to facilitate the use of microsimulation as a methodology to incorporate natural capital in policy assessments that rely on farm income modelling. This is achieved by extending an existing farm-level geospatial microsimulation model (SMILE) to incorporate environmental and agronomic variables and thus improve the consistency of farm incomes with the underlying natural capital in local areas.

Geospatial farm level microsimulation

The field of farm level geospatial microsimulation modelling is primarily concerned with the geospatial incidence of farm level variables (O'Donoghue, 2017b). Geospatial microsimulation models use a matching process to take a micro-dataset and make it consistent with small-area calibration data (Tanton, 2014; O'Donoghue et al., 2014), in order to generate a dataset that is representative both of the farm-level information contained in the micro-dataset and the geospatial information from the geospatial calibration data. Essentially the approach involves either reweighting the micro-data to make it consistent with geospatial calibration totals taken from Census or Administrative calibration data (Tanton and Vidyattama, 2010), or sampling of the micro-data according to sample quotas derived from the geospatial calibration data (Farrell et al., 2013).

In this paper we utilise the Simulation Model of the Irish Local Economy (SMILE-Farm) (O'Donoghue et al., 2013; 2017a), which generates a geospatial distribution of farms that is consistent with small-area data in terms of farm size and system and the contextual data in the Teagasc National Farm Survey (NFS) which is nationally representative by farm size and system and is the basis of the Irish data provided annually to the European Commission Farm Accountancy Data Network (FADN). There have been a number of variants of the SMILE model. Hynes et al., (2009b) describe the SMILE model's construction and calibration using simulated annealing, linking the 2000 Census of Agriculture with the Teagasc NFS (Ballas et al., 2005; Shrestha et al., 2007). O'Donoghue et al. (2017a and 2012) utilised the less computationally intensive Quota Sampling (QS) (Farrell et al., 2013) to link the NFS to the 2010 Census of Agriculture. QS is a probabilistic reweighting methodology that reweights survey data according to chosen constraint totals for individual pre-defined small areas.

SMILE re-samples from the Teagasc NFS which contains detailed farm level management and income characteristics to be consistent with geospatial agricultural information contained in the Census of Agriculture (collected every 10 years or administrative data (produced annually). The calibration totals reflect the main variables associated with farm-level outcomes including farm system, size and an aggregated soil type. However the incorporation of heterogeneous variables could improve the geospatial resolution and representativeness of the model in relation to local environmental attributes.

In order to understand how improved geospatial environmental characteristics might improve the model, we consider an example. Take two similar sized dairy farms, one on well-drained soils in the South West with a long grass growing season because of milder, drier weather conditions and a similar dairy farm in the North East, on heavy, wet soils with a shorter grass growing season. As outlined in table 4.1 the former will likely have a higher stocking rate and lower purchased feed requirements than the latter. In order for SMILE to be able to differentiate between these different environmental contexts, additional information in relation to the condition of local natural capital is required.

In sampling or reweighting from a national survey to be consistent with small area data of a census database, one option is to sample for farms within a particular region from farms of that region. However, O'Donoghue (2017b) found that the performance of the matching algorithm was poorer than when sampling from a regional sample pool. This arises as the number of cells of farm size by farm system reduces when allocated across regions, resulting in a poorer match. Thus an alternative approach is required to adjust data post-sampling according to differences in agronomic and environmental factors.

Conditional Independence of Matching in Geospatial Simulation

The conditional independence assumption is a necessary condition for any statistical matching or enhancement procedure (D'Orazio et al., 2006). Geospatial microsimulation is in effect a statistical matching process, calibrating a series of overlapping variables between the micro survey and the calibration totals and the incorporating other non-overlapping geospatial variables from the Census or other geospatial dataset into the micro dataset. In a farm-based geospatial microsimulation model, the overlapping variables are farm characteristics, while we import geospatial attributes into the micro data. As highlighted above, the local environment informs the distribution of stocking rate of animals and the nature of the feed and fertiliser inputs used on a farm.

More formally, consider two datasets, say A and B with sets of variables (X, Y) and (X, Z) respectively. Statistical matching involves matching two datasets together by finding units in sample B with similar values of the X variables in sample A, to produce a new dataset (X, Y, Z). Implicit in this method is finding a distance function D (X_A, X_B) where the match is found when the distance is minimised for the set of overlapping variables X (Rodgers and DeVol, 1981). In terms of geospatial microsimulation, A is the geospatial dataset where Xs are the overlapping variables used for matching and Zs are the geospatial attributes, while sample B is an attribute-rich dataset such as an income survey (O'Donoghue, 2017b).

The assumption outlined in Rodgers and DeVol (1981) is that the conditional distribution of Z given X is independent of the conditional distribution of Y given X. This assumption is known as Conditional Independence. The Variance-Covariance matrix for these datasets can be defined as Equation 3:

$$C = \begin{pmatrix} Cov(X,X) & Cov(X,Y) & Cov(X,Z) \\ Cov(Y,X) & Cov(Y,Y) & Cov(Y,Z) \\ Cov(Z,X) & Cov(Z,Y) & Cov(Z,Z) \end{pmatrix} \qquad (3)$$

Each of these co-variances can be measured using either dataset, except for $Cov(Y,Z)$ and $Cov(Z,Y)$. It is assumed that these covariances are zero. In our geospatial microsimulation model, the relationship between our non-overlapping variables Y and our geospatial variables Z is uncorrelated once we condition on the matching variables. Thus, we are assuming that the geospatial incidence of Y is fully accounted for by the geospatial distribution of our X variables.

However, this assumption does not always hold, so essentially there is geospatial heterogeneity of variables of interest, independent of the correlation with the overlapping or matching variable X. Based on this equation, the combination of matching variables (farm characteristics) and overlapping variables (variables of interest) don't necessarily represent the combination of matching variables (X), overlapping variables (Y) and geospatial variables (Z).

Therefore, when sampling variables such as farm system and farm size from a survey dataset using control totals of a census dataset and matching with geospatial environmental variables, it is assumed that the conditional independence of this matching is intact and that all geospatial interactions of other variables are incorporated in these matches (O'Donoghue et al. 2014, 2010). However, this paper argues that the failure to incorporate geospatial environmental and agronomic factors within the match leads to a failure of the conditional independence. A common weakness in existing geospatial models is that the re-sampling or reweighting processes used in their generation don't fully incorporate geographically varying agronomic and environmental variables (Hynes et al., 2009a; Morrissey et al., 2008).

Specifically, as highlighted in table 4.1, if the local environmental characteristics are not accounted for, the livestock density in areas with poor natural capital will be over-estimated, while purchased feed requirements will be under-estimated and *vice versa*. As a result, the conditional independence assumption fails, because farms with higher livestock density can be located in good or bad soils that are not conditionally dependent on each other. Thus the match algorithm smooths the relationships, diminishing the actual heterogeneity and under-stating geospatial variation of farm activity, by in effect understating the importance of natural capital in production. This means that the linking of overlapping variables with agronomic and environmental variables should be based on a specific location rather than a region or a theoretical condition.

The consequence of sampling without incorporating the local environmental and agronomic context is that sampled results will not be accurate for geospatially varying agronomic and environmental contexts. A correction mechanism to account for this failure is needed to improve the geospatial reliability of the data so as to enable us to analyse the impact of agronomic and environmental factors on farm market (gross) margin, a commonly-used measure of farm income.

In addressing the unexplained heterogeneity problem arising from the failure of the conditional independence assumption, increasing the number of overlapping variables is considered. However, it is not feasible to increase the number of constraints or to focus on regional scale (as it worsens the performance of the model/results (O'Donoghue et al. 2014, 2018; O'Donoghue, 2017b). Focusing on a regional scale is not ideal, because the agronomic and environmental situation is more granular than the region and even a very small region can have variation in localised environmental conditions.

Therefore, as it is not feasible to use an approach that avoids the conditional independence assumption, an approach that corrects for the failure of this assumption is needed. This is undertaken by creating a series of production and cost functions that account for the conditional covariance of farm characteristics and agronomic situations, conditional on overlapping variables, namely an Income Generation Model that adjusts for agronomic and environmental factors.

Natural Capital Based Income Generation Model

An income generation model is a system of equations that defines the drivers of different components of income. In the context of a farm level model, components of farm market gross output (output before subsidies are paid), such as dairy, cattle, sheep and tillage market gross output are included. Tillage farms generally have multiple crop enterprises for rotation purposes and can also provide input into livestock systems.

Early papers on income generation models were based on wage comparisons and distributions (Blinder, 1973; Oaxaca, 1973; DiNardo et al., 1996). A study by Winters et al. (2002) carries out the income generation process for crop, livestock, agricultural and non-agricultural wages. Rahman et al. (2017) use an Alternative Income Generating Activities model to analyse net monthly income of households relying on non-forestry sources of earnings.

In the geospatial microsimulation model described in this paper, a panel data model is utilised for farm variables in a form other than binary form, so the production ($\frac{V_{i,t}}{lu_{it}}$) and cost functions ($\frac{X_{CV}^{i}}{ha_i}$) take the following forms, respectively (Equation 4, 5):

$$\frac{V_{i,t}}{lu_{it}} = f_i\left(p_{M,t}^{i}, W_{CV,t}, A_{it}, K_{it}, L_{it}, X_{it}, ha_{it}, lu_{it}, u_i, \sigma_{it}/\alpha, \beta, \upsilon, \delta, \mu\right) \quad (4)$$

$$\frac{X_{CV}^{i}}{ha_i} = g_i^{l}\left(W_{CV,t}, A_{it}, K_{it}, L_{it}, X_{jt,j\neq i}, V_{it}, ha_{it}, lu_{it}, u_i, \sigma_{it}/\alpha, \beta, \upsilon, \delta, \mu\right) \quad (5)$$

where u_i is permanent and σ_{it} is transitory effects. The production function ($\frac{V_{i,t}}{lu_{it}}$) is defined as farm output divided by farm livestock unit in order to adjust for high output and low output farms that are mainly impacted by animal numbers. The cost function ($\frac{X_{CV}^{i}}{ha_i}$) is calculated as farm variable (direct) costs divided by farm utilised agricultural area to provide variable costs per farm size (hectare).

The technical efficiency element (A_{it}) of the model is affected by agronomic conditions and environmental factors (E_{it}), the quality of a land (Q_{it}), access to technical knowledge (H_{it})

and involvement in activities, e.g. environmental or forestry schemes and off-farm employment (O_{it}). If A^*_{it} represents efficiency and managerial skill, then:

$$A_{it} = A^*_{it} \times E_{it} \times H_{it} \times O_{it} \times Q_{it} \qquad (6)$$

$$A_{i0}, K_{i0}, L_{i0}, X_{i0}, ha_{i0}, lu_{i0}$$

where $A_{i0}, K_{i0}, L_{i0}, X_{i0}, ha_{i0}, lu_{i0}$ are initial states of technical efficiency, capital, labour, remaining inputs, utilised agricultural area (hectare) and livestock unit. The model draws a random number in order to account for the random noise σ_{it}. Then it simulates each of the dependent variables in turn. For simplicity, the estimation and simulation of all of the equations are carried out independently (O'Donoghue, 2017b).

As part of the Income Generation process, sampling needs to be conditioned on environmental and agronomic characteristics, to avoid biases and improve accuracy in the target variable of farm gross output.

In the first case, sampling is carried out without adjustment for agronomic and environmental variables (equation 7). While in the second case, while simulating samples, samples are adjusted to localised agronomic and environmental characteristics by means of changing Z_{orig} (original form) to Z' (adjusted form) based on the location of farms. Initially, the farm output results are calculated using equation 7, while equation 8 is used later to extract adjusted farm market margin from the calibration to localised agronomic characteristics (please see O'Donoghue (2017b) for model fitting information and validation procedures).

$$Y = \alpha + \beta Z_{orig} + \varepsilon_i \qquad (7)$$

$$Y' = \alpha + \beta Z' + \varepsilon_i \tag{8}$$

where Y is output without accounting for localised agronomic characteristics, Y' is market gross margin after taking into account localised farm context, α is the intercept, β is the coefficient of variables relating to natural capital (environmental and agronomic), Z represents the environmental and agronomic variables and ε_i is an error term.

Farm Market Gross Margin Inequality Decomposition

To evaluate the impact of the model, we compare the impact of the procedure on the geospatial heterogeneity of farm incomes, by comparing the intra and inter-area differences in the distribution of farm incomes. Examining the variability of incomes between farms within and across areas, inequality is decomposed into population sub-groups, where groups are areas. Total variability of incomes can then be decomposed into a factor attributed to between-group variability across space and variability within a district (within-group variability). Utilising the I_2 index, within-group variability is defined in equation (9), while between-group variability is defined in formula (10).[5] Utilising a population share $\left(1/n\right)$, we see that between-person inequality, is in fact the inequality of mean lifetime income.

$$I_w = \sum_j w_j I_j \tag{9}$$

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[5] Björklund and Merilä, 1997 use a similar decomposition method but instead use the I_0, Theil L and I_1 Theil T indices.

where $w_j = v_j^2 f_j^{-1}, v_j$ the income share of each person j and f_j is the population share of the person, in this case $\left(1/n\right)$.

$$I_b(y) = \frac{1}{2}\left[\sum_j f_j\left(\frac{\mu_j}{\mu}\right)^2 - 1\right] = \frac{1}{2}\left[\frac{1}{n}\sum_j\left(\frac{\mu_j}{\mu}\right)^2 - 1\right] = I(\mu) = \bar{I} \qquad (10)$$

where μ_j is the mean lifetime income for person j and μ the mean population lifetime income. The simulated data in SMILE is then used to compare the degree of between and within-geospatial district (county) inequality and examine the changes resulting from incorporating natural capital has on the level of both.

In order to see the level of change in farm market output within counties and among counties, the generalized entropy index is deployed (Shorrocks, 1980). The generalized entropy index can be used to measure the income inequality for a given dataset (Bourguignon, 1979). In this case, it is utilised to measure farm market output inequality within and between counties. The formula for the generalized entropy index is given in equation 11:

$$GE(\alpha) = \frac{1}{\alpha^2-\alpha}\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i}{\bar{y}}\right)^{\alpha} - 1\right] \qquad (11)$$

Data Sources

The geospatial microsimulation approach used here requires three datasets: a micro dataset of farms, geospatial farm calibration totals from the census and geospatial environmental characteristics. SMILE is calibrated to the sub-catchment level geospatial unit. There are 583 sub-catchments in Ireland within 46 river catchments.

Agricultural Administrative data

Geospatial microsimulation models require geospatial data to calibrate micro-data to be consistent with local geospatial patterns. In this version of the model, given a 10 year gap between Census of Agriculture totals, we utilise tabulations drawn from administrative data, the Animal Identification and Movement (AIMS) System and Land Parcel Information System (LPIS) maintained by the Department of Agriculture, Food and the Marine (DAFM), which records animal movements between herds, from birth to slaughter and contains information such as: calf birth by month, gender, sire type, number of beef and dairy calves, mart movement by month, gender and breed, as well as farm-to-farm movements cattle disposals and age profile of herds and are published annually (DAFM, 2017b).

AIMS provides detailed animal numbers for local geospatial areas. AIMS farm types are classified as specialist beef production, specialist dairy, specialist sheep, mixed grazing livestock, specialist tillage, etc. Land use is recorded in the national LPIS geospatial dataset created by merging aerial photographs and images from satellites. Each land parcel has its own unique identification number that can be used to track attached attributes (LPIS, 2014). Characteristics such as the parcel identification number, herd number, digitised parcel area, crop description, whether a parcel is commonage or not, and claimed crop area (for subsidies) can all be found in Irish LPIS data (Zimmermann, 2016).

Farm Survey Data

The survey dataset is required for two purposes, as part of the base sampling or matching process, standard in geospatial microsimulation and in the case of this paper, to enable the estimation of an income generation model. A specific requirement of the latter purpose is that the data is georeferenced so that environmental data can be combined with the Teagasc NFS

The primary data source for the model is the Teagasc NFS for 2014 consistent with the administrative control totals. It is a voluntary survey, conducted as a part of the European Commission Farm Accountancy Data Network (FADN) and is used for policy, research, financial and performance measurement purposes (Teagasc, 2017).

The main variables collected in the survey are costs, subsidies, purchases, assets, liabilities, yields, inventories and sales. Farms in the survey are characterised as dairy, cattle rearing, cattle other, sheep and tillage systems. Because of the small number of farms, poultry and pig systems are not represented in the Teagasc NFS.

The FADN datasets have been referenced since about 2015 but have as of yet not been released for research purposes. A novel feature the Teagasc NFS is that historical data were georeferenced using address data. This process was particularly difficult given the imprecision of Irish addresses prior to the introduction of post codes in 2014 as described by Green and O'Donoghue (2013). However, this geo-referencing process allowed for local environmental variables such as rainfall, temperature, altitude, detailed soil codes etc. to be extracted from GIS databases.

Representativity

From 2014 onwards, farms below €8,000 Standard Output (SO)[6] were not included in the Teagasc NFS sample. The 2014 NFS survey represents 78641 farm holdings with 93% of sectoral output, however, about 60000 small farms recorded in the Administrative data are not covered by the

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[6] A standard output of €8,000 represents the equivalent of 6 dairy cows, 6 hectares of wheat or 14 suckler cows.

survey. Thus, although most output is covered in the NFS, approximately 20% of the land area is not covered[7].

These differences are highlighted in table 4.2, which presents the share of farms by system and size for both the survey and administrative data on which we develop our control totals. From a size perspective, 53% of farms in the administrative datasets are below 30 hectares, while less than 20% of the survey farms are in this bracket. Over 80% of the farms in the administrative data are cattle and sheep farms. Looking at livestock density, the farms excluded from the NFS have lower farm size, livestock density and consequently lower SO; hence their exclusion. Looking at system, dairy farms are over-represented in the survey by virtue of their higher output. However, 12% of farms in the administrative survey contain land, but no animals or tillage crops, as these farms are used for rental, silage production or grazing, with limited economic output.

In developing this model, it is important that the under-represented farms or non-represented farms are included. To do this, 'synthetic farms' are generated to represent missing farm types, (mostly cattle and sheep farms). To produce clones, farms under 50 hectares in the survey are replicated, adjusting all variables to a smaller farm size. For other pasture-only farms, we sample according to the size distribution and set their activity to zero, (bar land rental and silage costs).

Table 4.2. Comparison of Survey and Administrative Data

	NFS					Administrative Data				
system	<= 20 Ha	20-30 Ha	30-50 Ha	50+ Ha	Total	<= 20 Ha	20-30 Ha	30-50 Ha	50+ Ha	Total
Dairy	1.1	2.4	11.1	20.8	35.4	0.4	1.1	3.6	6.1	11.2
Cattle Rearing	0.7	3.4	6.6	4.4	15.1	7.6	3.9	4.2	1.9	17.5
Cattle Other	2.5	3.6	7.8	11.4	25.4	15.7	7.6	8.5	5.6	37.5
Sheep	1.4	1.7	4.0	5.8	12.9	4.8	2.0	2.6	2.4	11.9
Tillage	0.5	1.0	1.4	5.7	8.6	2.2	1.1	1.7	2.6	7.7
Mixed	0.0	0.2	0.3	2.1	2.6	0.6	0.3	0.4	0.6	2.0

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[7] This total depends upon how the NFS is weighted.

Other Pasture Farms (Rental, Silage, Grazing)	0.0	0.0	0.0	0.0	0.0	5.0	0.7	0.5	6.2	12.3
Total	6.2	12.3	31.2	50.3	100.0	36.3	16.7	21.5	25.4	100.0

Environmental and Agronomic Variables

The agronomic and environmental variables that are used in SMILE are grass growth rate, grass land cover, continentality (region's climatic difference), rainfall, temperature, region, distance to sea, the principal soil type and physiological land characteristics. In relation to soil quality, 'Soil1' represents areas with 'good' soils, i.e. soils of wide and moderately wide use ranges. Soil2 identifies medium soil quality with somewhat impeded drainage, while Soil3 represents poorer soils with limited agricultural use. These variables are in binary form, with 1 having an association and 0 otherwise.

Grass is the main source of feed for animals in outdoor farming systems. Spring grass growth rate and grass cover variables (table 4.3) are taken from satellite observations of grass growth during the spring season (Green et al., 2018). Rainfall and temperature data are provided by the Irish weather agency (Met Eireann).

Table 4.3. Summary Statistics of Agronomic & Environmental Variables

Variable Name	Mean	St. Dev	Min	Max
Spring grass growth rate (dry matter kg/ha)	9.33	6.36	-19.37	30.32
Spring grass cover (ha)	6500.25	728.79	3176.46	8575.78
Mean Rain (annual average, mm)	107.64	23.80	60.25	246.47
Mean Temp (annual average, °C)	9.07	0.60	4.67	10.76
Soil1 (binary)	0.17	0.37	0	1
Soil2 (binary)	0.81	0.39	0	1
Soil3 (binary)	0.01	0.12	0	1

Independent and Dependent Variables

The independent variables included in SMILE are farmer age, farm size, family unpaid labour, dairy forage area, cattle forage area, sheep forage area, dairy livestock units, cattle livestock units, sheep livestock units, mean rainfall, mean temperature, continentality, distance to sea, land physiology, principal soil types and spring grass growth. Table 4.4 presents both simulated and sampled farm gross margin and gross output. All values are in Euro. It can be seen that the means of the simulated and sampled values are relatively close to each other, while standard deviation, maximum and minimum values have comparatively wider gaps.

Table 4.4. Sampled and Simulated Dependent Variable (Summary Statistics)

	Variable	Obs	Mean	Std. Dev	Min	Max
Sampled Gross Margin (€)	farmgm_ha	111,369	483.27	705.46	-1185.02	13377.3
Simulated Gross Margin (€)	si_farmgm_ha	111,369	483.24	802.28	-6325.19	74604.22

4.4. Results

This section presents the impact of amending matched data in the geospatial microsimulation model to highlight the impact of adjusting to account for localised natural capital.

Farm Income Differentials by Natural Capital

As context, we consider how farm market incomes vary by measures of natural capital. We focus on market income as measures of net income incorporating farm subsidies which tend to mitigate agronomic differences due to subsidies that account for natural capital such as the Areas of Natural Constraints (ANC) scheme[8].

The relationship between soil quality and farm market incomes in the geo-referenced Teagasc NFS is presented in Figure 4.1. In general, better-quality soils such as acid brown earths, brown podzolics and grey-brown podzolics enable higher stocking densities and are more productive in relation to crop and grass growth and consequent output and farm margin. Poorer soil types, e.g. organic (peat) soils and stony (lithosols) limit farm productivity and consequent economic performance. Higher stocking rates allow for high value systems such as dairy farming. Drier, flatter fertile land allows for high yields and machine trafficability, enabling tillage farming to be undertaken.

In tables 4.8 and 4.9 (appendix), this relationship is generalised using a multi-variate regression model of market gross margin per hectare against the variables used as a proxy for natural capital in this paper. It also reports summary statistics in relation to the natural capital variables in SMILE and the base survey, the Teagasc NFS. The former represents the natural capital variables of all agricultural land, while the latter represents the natural capital characteristics of areas where the largely higher output farms on typically better land are located (see Green et al., 2018).

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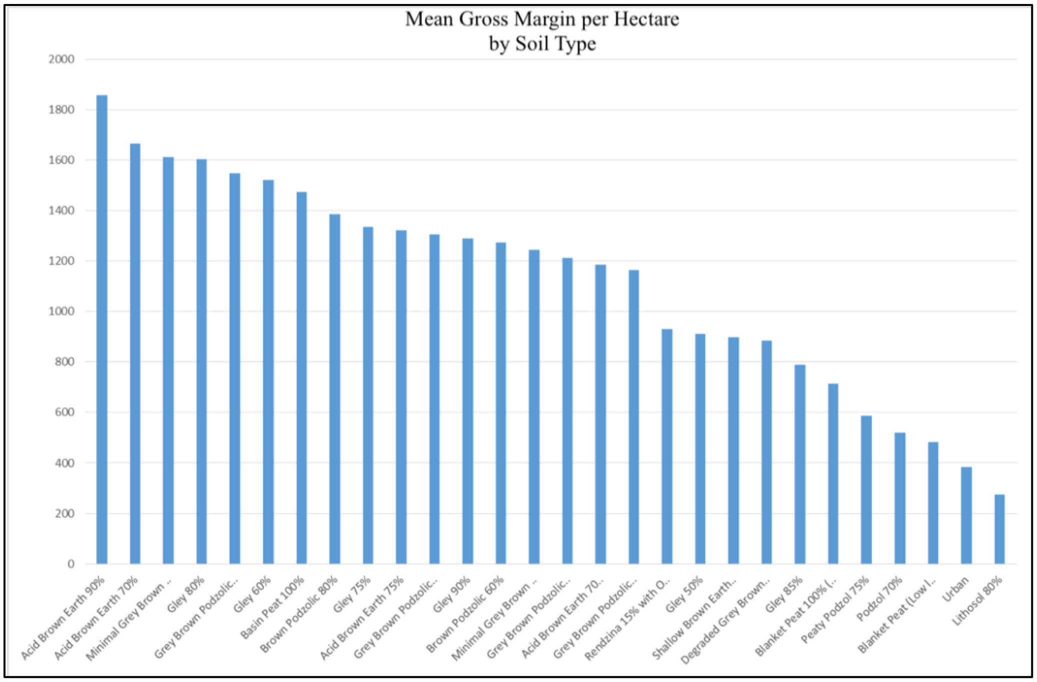
[8] The ANC scheme provides payments to people farming land in designated areas face significant hardships from factors such as remoteness, difficult topography, climatic problems and poor soil conditions. https://www.gov.ie/en/service/13d971-areas-of-natural-constraint-scheme



Source: Author calculations using Teagasc NFS (2014)

Figure 4.1. Monthly Mean Gross Margin per Hectare by Soil Types (€)

Applying the survey estimated coefficients to the real geospatial pattern of natural capital and the surveyed farms allows for the calculation of the differential impact of natural capital variables. The SMILE dataset has 14% lower market gross margin per hectare (€972) than the Teagasc NFS (€1199). This difference is expected, given that the NFS is sampled on better land and by definition with better farms[9]. It implies that the distribution of land in general as represented by all farms is worse than the survey data, consistent with Green and O'Donoghue (2013). This highlights the challenge if natural capital is not accounted for when generating the base dataset of the model.

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[9] It should be noted that while the farms are consistent with the distribution of farms, they are not actual farms from the administrative data, but rather farms sampled from the actual NFS. The clone farms to have a geospatial and distributional pattern consistent with the administrative data.

The Geospatial Distribution of Farm Gross Margin with and without Environmental Calibration

The initial match is generated by sampling the adjusted NFS using the calibration totals from the administrative data according to size and system. The geospatial distribution of the market gross margin per hectare is reported in map (a) in figure 4.2 and in column (A) in table 4.5. The results are consistent with largely better land and higher incomes South and East of a line from Northeast to South West, observed by Commins and Frawley (1996). This pattern is a reflection of the sampling by size and system from the adjusted survey according to the geospatial control totals. However, this regional difference ignores the variations in natural capital identified in table 4.1 above.

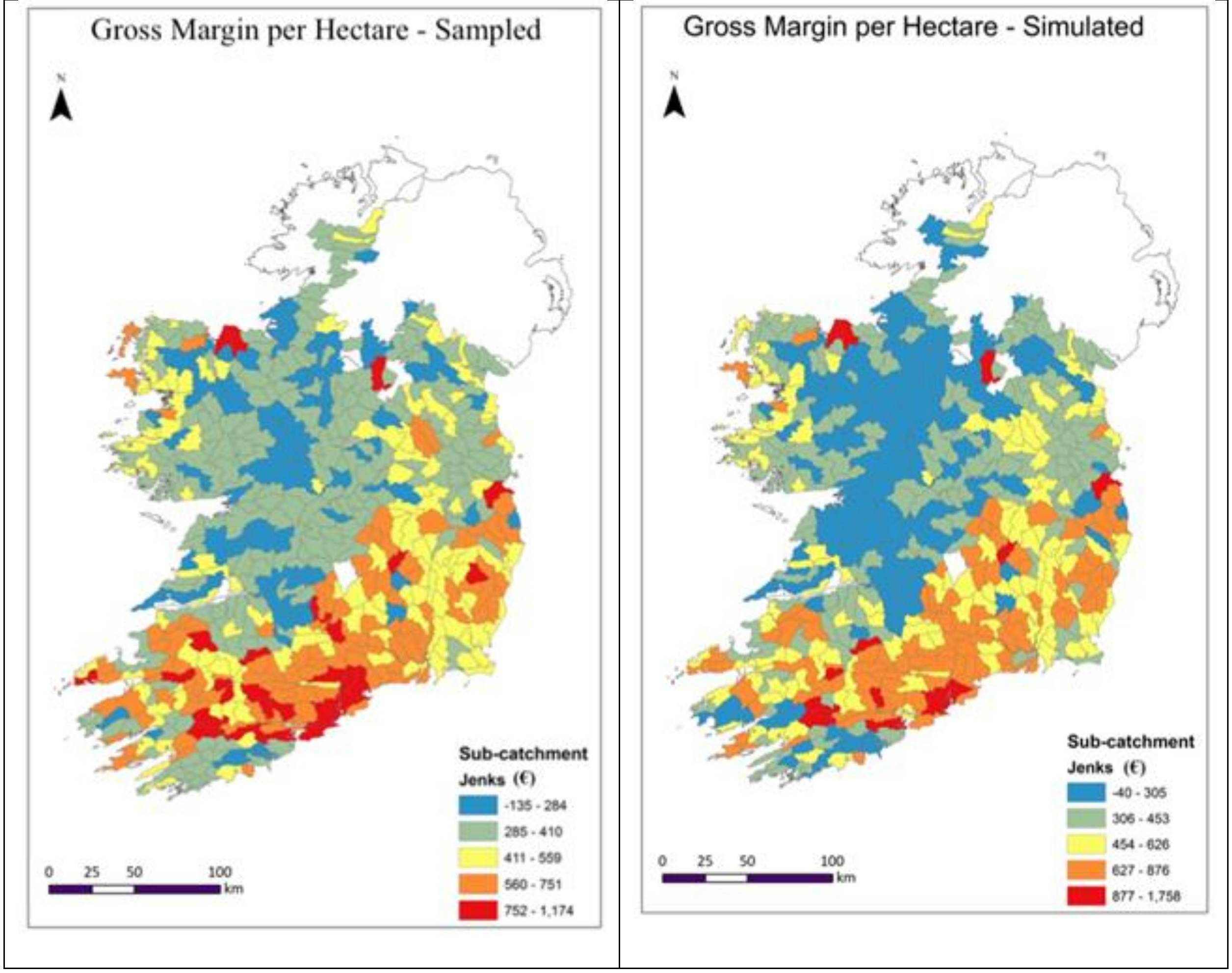
Figure 4.2 maps these differences, contrasting simulated and sampled results, and highlighting how natural capital factors impact farm market gross margin. The main impacts of agronomic and environmental calibration are seen around the midlands, the West and North-West.

The sampled map (a) represents differences in size and system, without taking additional natural capital drivers into account. We see that the North-West, South and South-East farms have a relatively higher gross margin per hectare, while the Midlands, North and North-East farmers have lower gross margins. This contrasts with the simulated map (b) which incorporates natural capital drivers. The simulation results have relatively higher upper bound values in the South and South-East.

Table 4.5 reports the average market gross margin per hectare before (sample) and after (simulated) adjustment. The lowest incomes occur in County Leitrim in the Northwest in both cases. This reflects the location of lower production systems in this area due to the poor agronomic condition (sample) and due to the relative difference in extent (simulated). As noted above, as the sampling accounts for system differences, which are in part based on ecosystem condition, the impact of the natural capital simulation primarily relates to within-system differences. The bottom seven counties in terms of income are all located in the West, Northwest or Border regions, with mainly low-income sheep and cattle rearing systems. The ordering is not monotonic, reflecting the underlying ecosystem condition differences, with the addition of the natural capital variables making the biggest difference in Counties Donegal and Roscommon.

At the top of the distribution are counties of the ‘Golden Vale’, Tipperary, Limerick and part of Cork and other counties in the South such as Waterford and Kilkenny. These counties have significant dairy sectors, the highest income farming system. Broadly their rank remains the same across the sampled and simulated results, with Limerick and Tipperary swapping place. The counties in the middle of the distribution are counties in the midlands with a combination of cattle finishing, tillage and some dairy farms.

Table 4.5 also tabulates the impact of the adjustment due to natural capital condition differences. The adjustment at county level varies from an increase of 11% (Waterford in the SW) to a decrease of 23% (Leitrim in the NW). Of all counties, Kerry in the Southwest and Donegal in the North West have the biggest falls in rank, falling 5 and 4 places respectively once ecosystem condition is accounted for. Both are coastal counties with relatively large areas of poor land, but with varied farm systems, including some dairy farms. In general, the counties in the East, Midlands and Southeast have the highest adjustment, with the North-West having the largest reduction. These are consistent with differences in grazing season length, which is driven by natural capital characteristics (Green et al., 2018).


(a) Sampled Market Gross Margin per Hectare

(b) Simulated Market Gross Margin per Hectare

Figure 4.2. Market Gross Margin (€) per Hectare Sampled and Simulated (based on Jenks or Natural Breaks Classification)

Figure 4.3 represents the county-level variation of the farm (market) gross margin before and after adjustment for natural capital variables. It can be seen that in the South-East and East of Ireland, there is an increase of up to 5.7% in the farm gross margin. In contrast, the North and South-West of the country see up to a 27.1% decrease in market gross margin. At the same time, the Irish midlands county-level results don't show a significant change after the inclusion of natural capital variables in the model and, on average, shown only a slight increase in farm gross margin.

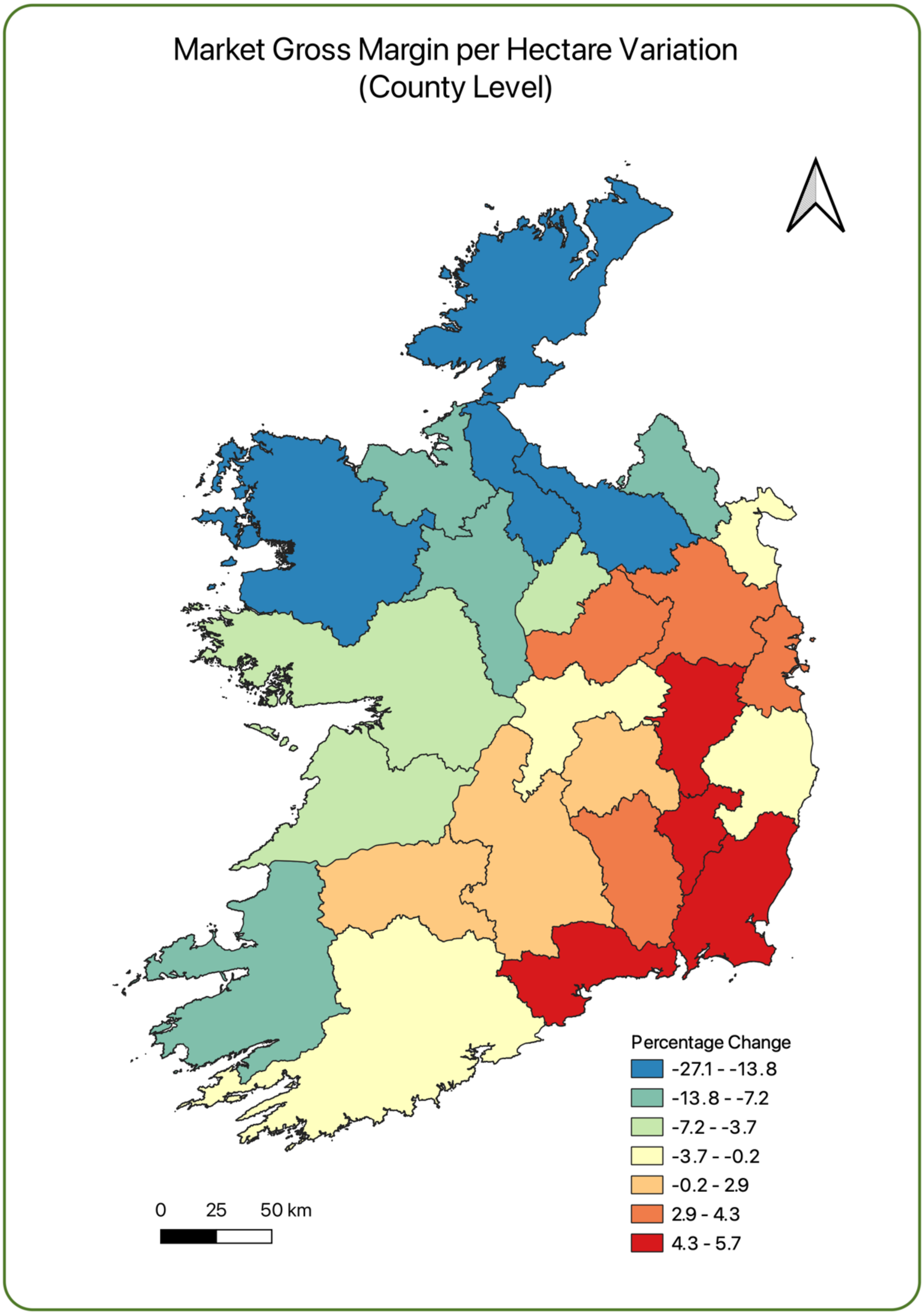


Figure 4.3. Market Gross Margin per Hectare Variation (€)

Table 4.5. Average Changes at County level for Sampled and Simulated Market Gross Margin per Ha

		Market Gross Margin per Ha (€)		Market Gross Margin per Ha relative to national average (€)		Ratio	
		Sampled	Simulated	Sampled	Simulated		
County	Region	A	B	C	D	D/C	B/A
Carlow	SE	1094.6	1147.8	1.13	1.24	1.10	1.05
Cavan	NW	860.2	735.7	0.89	0.79	0.90	0.86
Clare	MW	760.4	722.5	0.78	0.78	1.00	0.95
Cork	SW	1617.8	1584.1	1.67	1.71	1.03	0.98
Donegal	NW	688.8	515.7	0.71	0.56	0.79	0.75
Dublin	E	902.2	935.2	0.93	1.01	1.09	1.04
Galway	W	655.0	626.0	0.67	0.68	1.00	0.96
Kerry	SW	1129.3	996.2	1.16	1.08	0.93	0.88
Kildare	E	988.3	1033.6	1.02	1.12	1.10	1.05
Kilkenny	SE	1475.2	1528.0	1.52	1.65	1.09	1.04
Laois	M	1093.7	1093.8	1.13	1.18	1.05	1.00
Leitrim	NW	531.2	387.5	0.55	0.42	0.77	0.73
Limerick	MW	1384.3	1386.6	1.42	1.50	1.05	1.00
Longford	M	631.3	589.1	0.65	0.64	0.98	0.93
Louth	NE	933.6	905.9	0.96	0.98	1.02	0.97
Mayo	W	564.8	482.7	0.58	0.52	0.90	0.85
Meath	E	1030.0	1072.1	1.06	1.16	1.09	1.04
Monaghan	NE	837.8	725.7	0.86	0.78	0.91	0.87
Offaly	M	925.9	922.7	0.95	1.00	1.05	1.00
Roscommon	W	576.9	534.8	0.59	0.58	0.97	0.93
Sligo	NW	600.9	524.1	0.62	0.57	0.91	0.87
Tipperary	MW/SE	1380.2	1410.8	1.42	1.52	1.07	1.02
Waterford	SE	1564.9	1650.9	1.61	1.78	1.11	1.05
Westmeath	M	857.5	883.8	0.88	0.95	1.08	1.03
Wexford	SE	1490.0	1575.5	1.53	1.70	1.11	1.06
Wicklow	E	1127.7	1089.1	1.16	1.18	1.01	0.97
Total		971.6	926.4	1.00	1.00	1.00	0.95

NB: This analysis focuses on primarily on pastoral farms.
E – East; M – Midlands; MW – Mid West; NE – Northeast; N – North West; SE – South East; SW – South West; W - West

Our interest in the geospatial distribution of farm income relates to variation in natural capital or environmental attributes on the one hand, and the impact of agricultural activity on the other hand. In table 4.6, we decompose the variation of market gross margin per hectare across all farms into between-district (geospatial area) variation and within-group variation at the sub-catchment level.[10] It should be noted that between-group variation accounts for only about 9-10%

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[10] The algorithm was unable to process the analysis at the more disaggregated townland level

of the total variation of market gross margin per hectare; it is quite low, but consistent with other findings (O'Donoghue, 2017b). This reflects the greater variation between people than between places, reflecting those individual farmers makes individual decisions in relation to stocking rate, system and feed. Farmers also have different skills, efficiency and motivation.

In undertaking the geospatial adjustment, we find that the simulation method captures more variation, with overall variation increasing by 14% when using the Generalised Entropy measure and 5% when using the Gini. Between area variation increases by 23% as the model improves the geospatial relationship between agricultural income and the pattern of natural capital. Within-area variability also increases but at a lower rate of 13%, given that there are environmental differences within districts as well. Combining, we find that the share of variation accounted for by between-area variation increases by 8%. Within-area variation remains the most important source of variation.

Table 4.6. Within and Between Group variation in Market Gross Margin per Hectare.

	Base		igm3	
	GE (2)	Gini	GE (2)	Gini
Total	1.056	0.677	1.207	0.712
Within	0.960		1.088	
Between	0.096		0.119	

NB: This analysis focuses on primarily on pastoral farms. The Geospatial unit is sub-catchment.

In Table 4.7, the statistical significance of the changes made by the simulation procedure to improve the relationship between agriculture and natural capital is reported. For all farms, the mean market gross margin per hectare falls by 5%, with the change in mean being significantly different from zero. The components of the market gross margin, output and direct costs, change by a similar percentage, maintaining the direct cost to output ratio at about 31%.

At a system level, the difference in stocking rate (intensity) and output per livestock unit (yield) on dairy farms, although significantly different from zero has the smallest change of 1% increase and a 2% decrease respectively. When combined into gross output, the changes balance out. This reflects the concentration of dairy systems on better land. The adjustment for natural capital has the highest impact for sheep farms as they occur both in upland areas and lowland areas (with very low stocking rates), with the biggest fall in intensity. This is because both the intensity and the yield of cattle farms fall by respectively 5% and 4%.

Table 4.7. Statistical significance of changes in Farm Market Gross Margin (€) per hectare and its components

	Sampled			Simulated		
	LB	UB	Mean	Mean	Ratio Simulated: Sampled	Statistically Different
All Farms						
Market Gross Margin per Ha	964	980	972	926	0.95	1
Market Gross Output Per Ha	1398	1418	1408	1336	0.95	1
Farm Direct Costs per Hectare	434	439	437	409	0.94	1
Dairy Farms						
Dairy Livestock Units per Ha	1.83	1.85	1.84	1.87	1.01	1
Dairy Gross Output per Livestock Units	1858	1869	1864	1822	0.98	1
Cattle Farms						
Cattle Livestock Units per Ha	1.33	1.34	1.33	1.26	0.95	1
Cattle Gross Output per Livestock Units	565	568	567	541	0.96	1
Sheep Farms						
Sheep Gross Output per Livestock Units	1.59	1.60	1.59	1.38	0.87	1
Farm Direct Costs per Hectare	464	469	466	441	0.95	1

NB: LB stands for Lower Bound and UB for Upper Bound. The Lower Bound represents the minimum level of gross output, gross margin, direct costs, etc. that farms have within the simulation, while the Upper Bound represents the maximum level of gross output, gross margin, direct costs, etc. The "Statistically Different" column with a value of 1 represents that the change in mean is significantly different from zero and has a probability of less than 5% of being random in terms of the mean being different from zero.

4.5. Discussion and Conclusion

This study develops a modelling framework to improve the capacity to incorporate the heterogeneity of agricultural systems associated with local natural capital characteristics, in geospatial microsimulation models. Existing farm geospatial microsimulation models do not directly factor in natural capital (agronomic and environmental) variables and as result have a tendency to under-estimate geospatial heterogeneity, which is an important element influencing costs and output. The modelling framework is then utilized to investigate the impact of natural capital on farm market gross margin.

In order to account for the geospatial heterogeneity of natural capital, we estimated an income generation model that incorporated physical capital, human capital and natural capital. Once the farm data are sampled in accordance with administrative data-based geospatial control totals, the sampled distribution was adjusted to account for the local natural capital characteristics by adjusting each component of the market output and costs. As the new geospatial distribution of natural capital characteristics is worse than the distribution within the survey, this adjustment has a tendency to reduce average incomes, reflecting the purpose and design of the farm survey used (which focuses on the representativity of output and not place). The results show the lowest incomes occur in West, Northwest or Border under either measure. This reflects both the fact that lower production systems are located in this area due to the poor agronomic condition (sample) and due to the relative difference in extent (simulated). The highest incomes occur in the South and Mid-West, consistent with findings in other studies. The biggest adjustments at county level occur in terms of growth 11% (Waterford in the SW) to a fall of 23% (Leitrim in the NW). In general, the counties in the East, Midlands and Southeast have the highest adjustment, with the North-West have the biggest reduction, consistent with grazing season length.

Decomposing the variation in income between- and within-districts, the majority of income variation occurs within-area, reflecting preferences, skills and attributes of farms and some differences in within-area natural capital. However, adjusting for heterogeneity in natural capital increases the total variation and in particular, between-area variation. The change in mean incomes resulting from this approach was statistically significant both in total and for individual income components, with the biggest changes occurring for sheep farms that are located on a variety of different land types and the smallest changes on dairy farms which are more likely to be concentrated on good land.

This paper contributes to the literature on agricultural and environmental modelling through the development of the capacity to incorporate natural capital. The paper also contributes to the field of geospatial microsimulation modelling through the advancement of modelling capacity by highlighting the importance of incorporating natural capital conditions and extent in the analysis of farm incomes and developing for its incorporation. Improving the relationship between agriculture and the local environment in economic models has the added benefit of usability for other purposes which rely on this relationship, such as analysis of environment improvement measures on farms and supporting policy frameworks. In order to enhance the model in the future by controlling the uncertainty of distributions of variables, Confidence Intervals could be used to offer more informative way to interpret results (Rahman, 2017; Veroniki, et al. 2016). However, the two-stage process of sampling and calibration makes it difficult, while the scale makes it quite a computation challenge.

Improved consistency between agricultural attributes and natural local capital drivers allows for policy analyses of measures to improve the environmental footprint of agriculture. It is also useful in understanding the local economic drivers of land use change to (for example) forestry and improves our understanding of the contribution of agriculture to rural development. This methodology is scalable as the Irish FADN data used in this paper are available in other countries and similar geospatial datasets exist in many countries. However, it does rely on geo-referenced farm survey data and on the release of geo-referenced farm survey data for research purposes.

Authorship

D. H. – conceptualization, methodology, investigation, resources and writing.

C. O’D. – validation, investigation, conceptualization, writing – review and editing.

M. R. – conceptualization, investigation, writing – review and editing.

C. Z. – supervision and revision.

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Conflicts of Interest

The authors declare there are no conflicts of interest.

Ethical Approval

Not applicable. Data used were from secondary data sources.

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Appendix

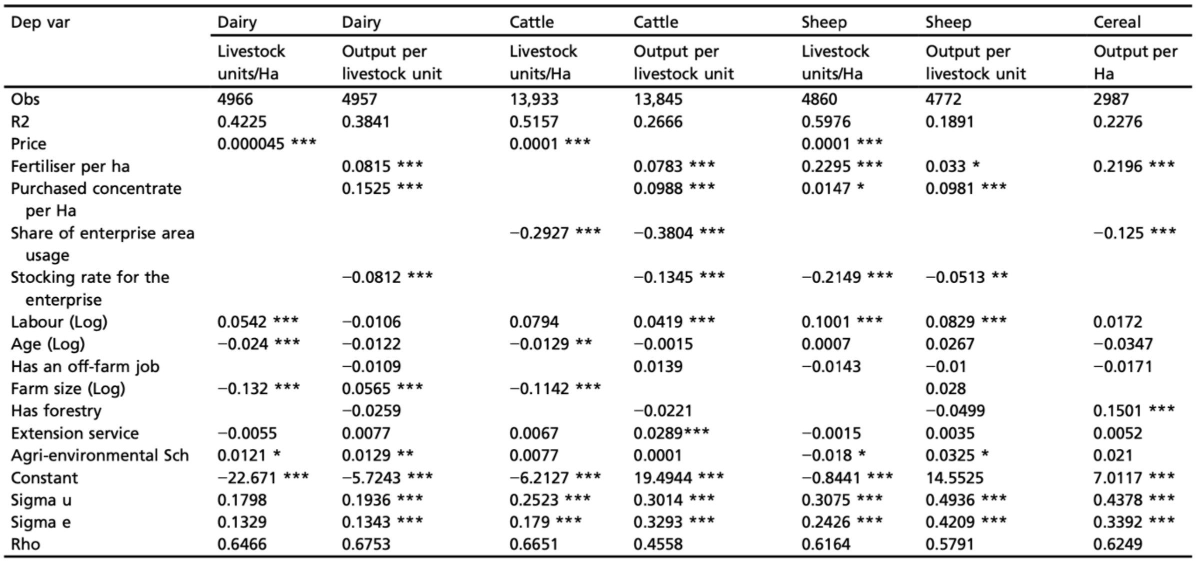
Table 4.8. Regression Model of Market Gross Margin per Hectare as a function of Natural Capital Variables

Explanatory Variables	Coef.	Std. Err.	t	Mean (Survey Data)	Mean (SMILE-GIS)
Acid Brown Earth 70%	0.3	0.3	0.92	0.006	0.000
Acid Brown Earth 70% (Coarse texture)	0.4	0.3	1.31	0.008	0.000
Acid Brown Earth 75%	0.5	0.2	2.05	0.040	0.000
Acid Brown Earth 90%	1.2	0.4	2.73	0.011	0.000
Basin Peat 100%	-0.6	1.5	-0.41	-0.010	0.000
Blanket Peat (Low level) 100%	-0.1	0.4	-0.28	-0.001	0.000
Brown Podzolic 60%	0.1	0.2	0.61	0.016	0.000
Brown Podzolic 80%	0.2	0.4	0.49	0.007	0.000
Degraded Grey Brown Podzolic 50%	-0.5	0.3	-1.68	-0.014	0.000
Gley 50%	-0.3	0.3	-1.08	-0.011	0.000
Gley 60%	0.2	1.5	0.13	0.002	0.000
Gley 75%	0.4	0.2	1.51	0.024	0.000
Gley 80%	0.1	1.5	0.08	0.002	0.000
Gley 90%	-0.4	1.4	-0.29	-0.019	0.000
Grey Brown Podzolic 60%	-0.1	0.3	-0.33	-0.004	0.000
Grey Brown Podzolic 70%	0.2	0.3	0.88	0.011	0.000
Grey Brown Podzolic 75%	0.3	0.3	1.01	0.009	0.000
Grey Brown Podzolic 80%	0.5	0.3	1.64	0.017	0.000
Island not surveyed	-0.9	0.4	-2.26	-0.011	0.000

Lithosols and Outcropping Rock 70%	0.8	0.2	3.57	0.084	0.000
Minimal Grey Brown Podzolic 70%	0.4	0.2	1.48	0.026	0.000
Peaty Gley 70%	-1.1	0.3	-4.18	-0.047	0.000
Peaty Podzol 75%	-1.2	0.5	-2.65	-0.010	0.000
Podzol 70%	0.4	0.7	0.59	0.001	0.000
Distance to Sea	0.0	0.0	-1.53	-0.112	0.000
Average Temperature	-0.1	0.0	-5.09	-1.144	0.000
Average Rainfall	0.0	0.0	-5.7	-1.673	0.000
Flat to Undulating Lowland (Mainly dry	-0.3	0.2	-1.11	-0.091	0.000
Flat to Undulating Lowland (Mainly wet	0.4	1.4	0.26	0.033	0.000
Hill	0.0	0.3	0.09	0.002	0.000

Source: Teagasc National Farm Survey and Simulation Model of the Irish Local Economy

Table 4.9. Gross Output Estimation



Dep var	Dairy	Dairy	Cattle	Cattle	Sheep	Sheep	Cereal
	Livestock units/Ha	Output per livestock unit	Livestock units/Ha	Output per livestock unit	Livestock units/Ha	Output per livestock unit	Output per Ha
Obs	4966	4957	13,933	13,845	4860	4772	2987
R2	0.4225	0.3841	0.5157	0.2666	0.5976	0.1891	0.2276
Price	0.000045 ***		0.0001 ***		0.0001 ***		
Fertiliser per ha		0.0815 ***		0.0783 ***	0.2295 ***	0.033 *	0.2196 ***
Purchased concentrate per Ha		0.1525 ***		0.0988 ***	0.0147 *	0.0981 ***	
Share of enterprise area usage			−0.2927 ***	−0.3804 ***			−0.125 ***
Stocking rate for the enterprise		−0.0812 ***		−0.1345 ***	−0.2149 ***	−0.0513 **	
Labour (Log)	0.0542 ***	−0.0106	0.0794	0.0419 ***	0.1001 ***	0.0829 ***	0.0172
Age (Log)	−0.024 ***	−0.0122	−0.0129 **	−0.0015	0.0007	0.0267	−0.0347
Has an off-farm job		−0.0109		0.0139	−0.0143	−0.01	−0.0171
Farm size (Log)	−0.132 ***	0.0565 ***	−0.1142 ***			0.028	
Has forestry		−0.0259		−0.0221		−0.0499	0.1501 ***
Extension service	−0.0055	0.0077	0.0067	0.0289***	−0.0015	0.0035	0.0052
Agri-environmental Sch	0.0121 *	0.0129 **	0.0077	0.0001	−0.018 *	0.0325 *	0.021
Constant	−22.671 ***	−5.7243 ***	−6.2127 ***	19.4944 ***	−0.8441 ***	14.5525	7.0117 ***
Sigma u	0.1798	0.1936 ***	0.2523 ***	0.3014 ***	0.3075 ***	0.4936 ***	0.4378 ***
Sigma e	0.1329	0.1343 ***	0.179 ***	0.3293 ***	0.2426 ***	0.4209 ***	0.3392 ***
Rho	0.6466	0.6753	0.6651	0.4558	0.6164	0.5791	0.6249

Source: O’Donoghue et al. (2017b)

5. CHAPTER FIVE: The Marginal Effect of Investment in Machinery, Livestock, and Buildings on Irish Agricultural Output and Costs

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To achieve economically sustainable and profitable farms, farmers must manage various factors that impact farm output and costs. Numerous factors can influence farms' output, including soil quality, environmental conditions, farm size, system, and farmers' experience. This study investigates the impact of investment increases and decreases on farm gross output, direct costs, and overhead costs in Ireland, utilizing the Deep Neural Networks method. The data source for this study is a farm survey of pastoral-based livestock systems from 1996 to 2018. The findings reveal that, on average, Irish farmers ranging from the second gross output decile to the fifth decile will experience an increase in their gross output of 9% to 12.6% if they increase their investment in machinery, livestock, and buildings by 10%. Surprisingly, farmers in the first, ninth, and tenth deciles will experience a decrease in their gross output of 7.7%, 0.05%, and

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3.77%, respectively, if investments are increased. This discrepancy may be attributed to the fact that the lowest and highest gross output farms primarily rely on subsidies and have already made substantial investments, respectively, resulting in a lack of positive response to investment increases. As expected, a 10% increase in investments leads to an increase in direct and overhead costs across most deciles, while a decrease in investments results in a decrease in overhead costs across all deciles. The findings of this paper emphasize the significance of farm investments in agricultural output and costs, providing valuable insights for agricultural policymakers and other stakeholders in making research-based decisions.

Keywords: Agricultural output, agricultural costs, machine learning, modelling in agricultural economics

5.1. Introduction

Farm businesses are significantly affected by agricultural output and costs, and scholars have extensively studied the factors that influence these aspects using various methodologies and datasets (Adesina and Djato, 1997; Hennessy and Heanue, 2012; Mishra et al., 2004; Tijani et al., 2006). However, one crucial aspect that remains underexplored in the existing literature is the potential effects of increasing or decreasing investments in farms on output and costs. This research paper aims to address this gap and shed light on the implications of changes in farm investments.

Most previous studies have employed linear models to analyze farm output and costs, lacking built-in validation testing. In contrast, our research paper employs a novel deep learning method to analyze investment variables such as machinery, livestock, and buildings' impact on farm gross output, direct and overhead costs. This approach leads to new findings in the realm of agricultural output, costs, and farm investments.

Understanding the factors that influence farm income (Fayama et al., 2022; Junaidu et al., 2021) due to investments is crucial for farmers seeking to maximize their profits and manage their expenses. Farm profit is determined as the difference between farm output and costs. Knowing these influencing factors can serve as a valuable decision-making tool for farmers and agricultural policymakers. For instance, they may need to consider influencing certain farm variables, such as investment (Ouedraogo et al., 2021) in livestock, buildings, or machinery. Additionally, when farmers have incentives to increase their farm area or make environmentally conscious decisions like reducing machinery usage to decrease pollution, understanding the impact of these changes on farm output and costs becomes crucial (Prager and Posthumus, 2010).

Bokusheva et al. (2009) examine the relationship between farm investments and the ratio of sales to capital, revealing that this ratio can significantly influence investment behavior. Carey and Zilberman (2002) explore the adoption of irrigation technology as an investment in farms, highlighting that farmers are more likely to invest in modern technologies if the expected future returns outweigh the expected costs. Towne and Rasmussen (1960) introduce the concepts of "farm gross product" and "gross investment" and demonstrate investment trends in relation to total farm output since the 19th century.

Weersink and Tauer (1989) analyze investment models specific to dairy farms in New York, finding that these farms tend to utilize existing capital for longer periods before making additional investments. Skevas et al. (2018) investigate the impact of various farm-related characteristics on investment decisions, identifying factors such as land tenure, liquidity, agricultural support payments, and age as the main drivers of investment likelihood. Hanrahan et al. (2018) study the profitability of pasture-based dairy farm systems, revealing that farm size, capital investment in machinery, and buildings per cow significantly affect farm net profit per hectare.

Existing research on the influencing factors of farm income and productivity justifies their methodologies and datasets (Parvin and Akteruzzaman, 2012; Strappazzon et al., 1995; Yee et al., 2004). However, these studies have not expanded their scope to conduct a comprehensive analysis of farm profit using different families of statistical and mathematical techniques, which would provide a broader understanding of the impacting factors. Moreover, the majority of papers in the literature rely on traditional methods, such as linear regression models with a predefined set of explanatory factors, often focusing on specific aspects like livestock well-being, economic effects of subsidies, or environmental impacts of fertilizers, without providing a detailed and comprehensive exploration of the various factors influencing farm profit (Clay et al., 2020; Magdoff et al., 2000; Smith and Siciliano, 2015).

This research paper conducts a comprehensive examination of the factors influencing farm gross output, focusing on farm investments, utilizing deep neural networks. The choice of this method stems from its unique methodology, allowing for accurate and validated output results. Scholars in the field have established this technique as one of the most reliable for making estimations and projections. By applying this approach, the study aims to assess the measured effect of farm investment variables on farm gross output, direct, and overhead costs, both after a 10% increase and a 10% decrease in investments.

This work contributes to the existing literature by conducting an advanced analysis of the impact of farm investments on farm output, direct, and overhead costs using a relatively novel methodology. It also compares the differences before and after the implementation of investments. The related work section provides an overview of relevant published literature in the field, while the methodology section outlines the reasoning behind the chosen approach. The data section details the Teagasc National Farm Survey panel dataset used in the study, and the results section presents the identified explanatory factors and their effects on farm profit. Finally, the conclusion section offers concluding remarks and reflections on the findings.

5.2. Methodology and Data

In this section, Deep Neural Networks are initially discussed, followed by an alternative method, the random forest regression model, with its advantages and disadvantages that could potentially be used. Later, the study's utilized data, Teagasc’s National Farm Survey, is explained.

Deep Neural Networks

Deep Neural Networks are a type of artificial neural network architecture characterized by the presence of multiple hidden layers (as depicted in Figure 5.1). These networks consist of an input layer comprising neurons that take values from predictive or explanatory variables (Larochelle et al., 2009; Montavon et al., 2018; Sun et al., 2018). The neurons in the hidden layers calculate their values as a sum of the values from the previous layer (or input values) multiplied by their corresponding weights. The final layer is the output layer, which also contains values estimated by the previous layers' neurons and their respective weights. In Figure 5.1, four hidden layers with five neurons each are shown, while the input layer has three neurons representing investment in machinery, livestock, and buildings, and the output layer has one neuron representing farm gross output, direct costs, or overhead costs. However, the number of hidden layers and neurons in the input, hidden, and output layers can vary depending on the specific configuration of the deep neural network. In this paper, the deep neural networks used consist of four hidden layers, each containing ten neurons.

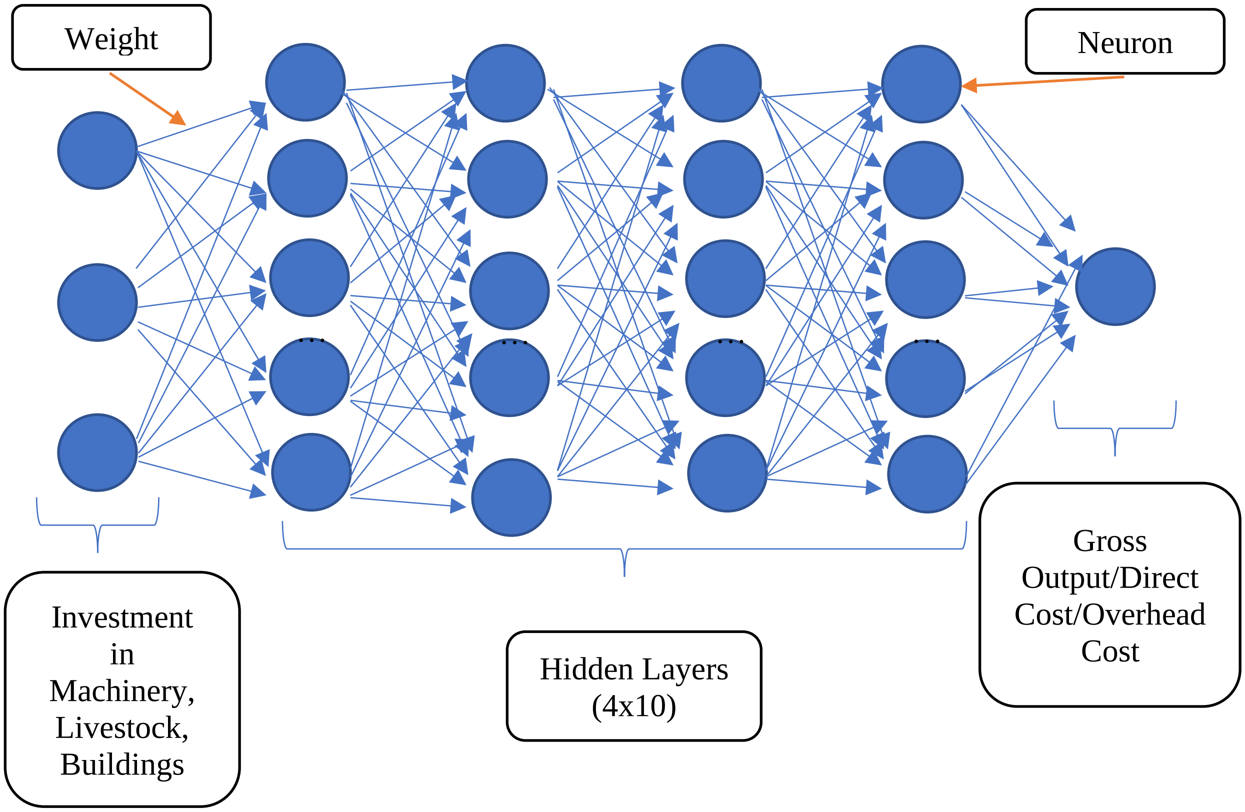

Figure 5. 1. Deep Neural Networks Structure

Initially, all weights are randomly assigned, and their related neurons are calculated; therefore, predicted outputs can be far from real/true/correct values. In order to reduce errors of weights within deep neural networks, deep neural networks will use the backpropagation technique (equation 1) to reduce errors and adjust weights so that in each iteration of prediction, errors are smaller and predicted values are more accurate.

$$\frac{\partial error}{\partial weight} = \frac{\partial a}{\partial weight} * \frac{\partial b}{\partial a} * \frac{\partial c}{\partial b} * \frac{\partial d}{\partial c} \ldots * \frac{\partial error}{\partial z} \tag{1}$$

$\frac{\partial error}{\partial weight}$ is the derivative ration of error to weight (or level of change in errors with respect to weights) and $a, b, c \dots z$ are a chain of neurons from the input layer to the output layer.

Activation functions are used within deep neural networks to facilitate convergence of neural networks to their optimal weights faster, determine the output values and format, and also impact the accuracy of predicted outputs. Activation functions are located within hidden layers, and they serve to activate or not activate neurons based on specific parameters/criteria. In the case of the sigmoid/logistic function, it compresses/squashes hidden layer neuron values into 0 to +1 values, where closer to +1 value suggests highly likely (activate) and 0 highly unlikely (don't activate). In comparison, the hyperbolic tangent (TanH) activation function has values between -1 to +1 and works better with neurons that have strong negative and strong positive values before conversation into TanH function neurons.

In this paper's analysis, rectified linear unit activation function for hidden layers and linear activation function for the output layer is used. The reasons for utilizing rectified linear unit function are that it is computationally efficient (neural networks converge faster), voids neurons that are not contributing, and the "infinite value range" issue if neurons contribute to the network. Equation 2 provides a simple yet effective equation of rectified linear unit activation function, where it returns either zero value for discontinued (not contributing) neurons or provided original value.

$$\varphi(\tau) = \max(0, \tau) \tag{2}$$

For the output layer, a linear activation function is used in order to keep all values in their given form and not confined to any value range. Equation 3 is a simple equation of linear activation function, where it has infinite positive and negative range.

$$\varphi(\tau) = \tau \tag{3}$$

The analysis of this study is carried output with the help of Python (version 3.7) programming language. And it utilized packages/libraries are Pandas, Numpy, Statsmodels, Sklearn, and Keras. The raw data is also prepared for the analysis in Python language.

One of the alternatives to the deep learning method is the random forest regression method, which was first introduced by Breiman (2001), and De'ath and Fabricius (2000). Random forests can be considered as a specific case of the concept of a random element in probability theory, involving a set of root forests with labeled vertices and a uniform probability distribution (2009). Lindner et al. (2015) later proposed a new method called random forest regression, which has gained popularity in various disciplines such as machine learning, pattern recognition, data mining, and applied statistics.

Random forests exhibit weak correlations between the solutions of their constituent trees due to the "injection of randomness" at two stages: the bootstrap stage and the random selection of features used in splitting tree nodes (Bokusheva et al., 2009). This method has been widely recognized and embraced by both the statistical community and researchers utilizing pattern recognition techniques, becoming one of the most popular methods for classification and non-parametric regression (Fanelli et al., 2011). Its popularity stems from not only its high classification accuracy but also other advantages it offers. However, for the current study, the deep learning networks were preferred due to their relatively advanced model training and testing capabilities, facilitated by their neural network architecture.

Data - Teagasc National Farm Survey

This paper will utilize data from the Teagasc National Farm Survey (NFS) collected between 1996 and 2018. The survey selects approximately 1000 farms each year based on Central Statistics Office quotas and assigns weights to ensure national representation of the Irish farm population. The survey is voluntary, and farms engaged in pig and poultry systems are excluded. It is part of the EU's Farm Accountancy Data Network (FADN) and serves various purposes, including policy, research, financial analysis, and performance measurement. The farms in the survey are categorized into dairy, cattle rearing, cattle other, sheep, and tillage systems. Due to the limited number of farms, poultry and pig systems are not included in the Teagasc NFS.

The survey collects various key variables, including costs, subsidies, purchases, assets, liabilities, yields, inventories, and sales. Table 5.1 provides summary statistics for the variables used in this study. Three variables of interest as explanatory factors are investment in machinery, livestock, and buildings. On the other hand, three other variables, namely farm gross output, direct costs, and overhead costs, will be influenced by changes in investments. These variables are presented as unweighted values, as the study aims to focus on the actual surveyed values per farm rather than weighted and nationally representative values.

Farm gross output is defined as total sales minus the purchase of livestock and crops, plus the value of farm produce used in-house, and receipts for hire work and service fees. Farm direct costs encompass costs directly associated with the production of all farm enterprises, such as dairy, cattle, sheep, and tillage. Farm overhead costs are expenses that cannot be directly allocated to a specific farm enterprise or production unit, often referred to as fixed costs.

Investment in machinery refers to the end-of-year valuation of machinery based on the replacement cost methodology. Investment in livestock is defined as the average of the opening and closing valuations of livestock. Lastly, investment in buildings refers to the end-of-year valuation of buildings based on the replacement cost methodology. The study does not consider the effects of public subsidies, climate change, farmers' mental health, different levels of farm asset depreciation, or other factors that can potentially influence both farm output, costs, and investments.

Table 5.1. Summary Statistics of Variables (€)

	Investment in Machinery	Investment in Livestock	Investment in Buildings	Farm Gross Output	Farm Direct Costs	Farm Overhead Costs
count	24611.00	24611.00	24611.00	24611.00	24611.00	24611.00
mean	32521.49	66675.09	42734.21	89493.94	31983.03	28339.65
std	46604.44	65797.65	60540.29	99424.31	44263.75	33552.11
min	0.00	0.00	-1431.06	0.00	0.00	-9508.39
max	1007385.00	836415.00	2049920.00	3339889.00	2676570.00	672717.00

5.3. Results

In this section of the paper, the validation of the deep learning model for the three dependent variables, namely farm gross output, direct costs, and overhead costs, is initially presented. This is followed by the results of the impact of increasing or decreasing investments in machinery, livestock, and buildings on our three target variables.

Tables 5.2-5.4 display the level of association between investment in machinery, livestock, and buildings with farm gross output, direct costs, and overhead costs, respectively. It is observed that investment in machinery and livestock shows a relatively high association with farm gross output compared to investment in buildings. For every one euro increase in machinery and livestock investments, farm gross output increases by 0.72 euros and 0.69 euros, respectively. However, with a one-euro investment in machinery, farm direct costs only increase by 0.17 euros, while in the case of livestock and buildings investments, they lead to direct costs increasing by 0.28 euros and 0.25 euros, respectively. Furthermore, if a farmer invests one euro in machinery, livestock, and buildings, they should expect overhead costs to increase by 0.39 euros, 0.13 euros, and 0.13 euros, respectively. These statistically significant correlation coefficients demonstrate a strong basis to estimate the impact of investment increase and investment decrease on farm output and costs using machine learning technique.

Table 5.2. Association of investment factors with farm gross output

	Coefficient	**Standard error**	**T-value**	**P-value**
Constant	3613.43	417.11	8.66	0.00
Investment in Machinery	0.72	0.01	92.07	0.00
Investment in Livestock	0.69	0.01	105.23	0.00

Investment in Buildings	0.38	0.01	54.57	0.00
R-squared	0.79			
F-statistic	30620			
Prob. (F-statistic)	0			
Log-Likelihood	-298990			
AIC	598000			

Table 5.3. Association of investment factors with farm direct costs

	Coefficient	Standard error	T-value	P-value
Constant	-2843.42	232.43	-12.23	0.00
Investment in Machinery	0.17	0.00	38.14	0.00
Investment in Livestock	0.28	0.00	77.28	0.00
Investment in Buildings	0.25	0.00	63.38	0.00
R-squared	0.67			
F-statistic	16580			
Prob. (F-statistic)	0			
Log-Likelihood	-284600			

AIC	569200

Table 5.4. Association of investment factors with farm overhead costs

	Coefficient	Standard error	T-value	P-value
Constant	1227.46	136.24	9.01	0.00
Investment in Machinery	0.39	0.00	152.41	0.00
Investment in Livestock	0.13	0.00	61.56	0.00
Investment in Buildings	0.13	0.00	57.65	0.00
R-squared	0.80			
F-statistic	33240			
Prob. (F-statistic)	0			
Log-Likelihood	-271450			
AIC	542900			

Validation of the Accuracy of the Model

Figure 5.2 displays the validation accuracy of our deep learning model, with farm gross output, farm direct costs, and farm overhead costs represented from right to left. The term "actual" refers to the actual data samples, while "testing estimation" indicates the deep learning model's estimated values for testing purposes. For example, 89,753.46€ represents the actual average farm gross output, while 84,772.27€ is the deep learning model's average estimation of farm gross output.

The overall accuracy is calculated to be approximately 94.12%, resulting in a mean absolute difference of -4,981.19€ for farm gross output. For farm direct costs, the overall accuracy is 90.87%, with a mean absolute difference of -2,682.36€, and for farm overhead costs, it is 95.42% with a mean absolute difference of -1,245.24€. In other words, the estimated farm gross output is, on average, 94.12% close to the actual farm gross output, while the closeness to farm direct and overhead costs is 90.87% and 95.42%, respectively. This estimation closeness is relatively good compared to the literature on machine learning models (Qin et al., 2017; Sambasivam and Opiyo, 2021) and general modelling field.

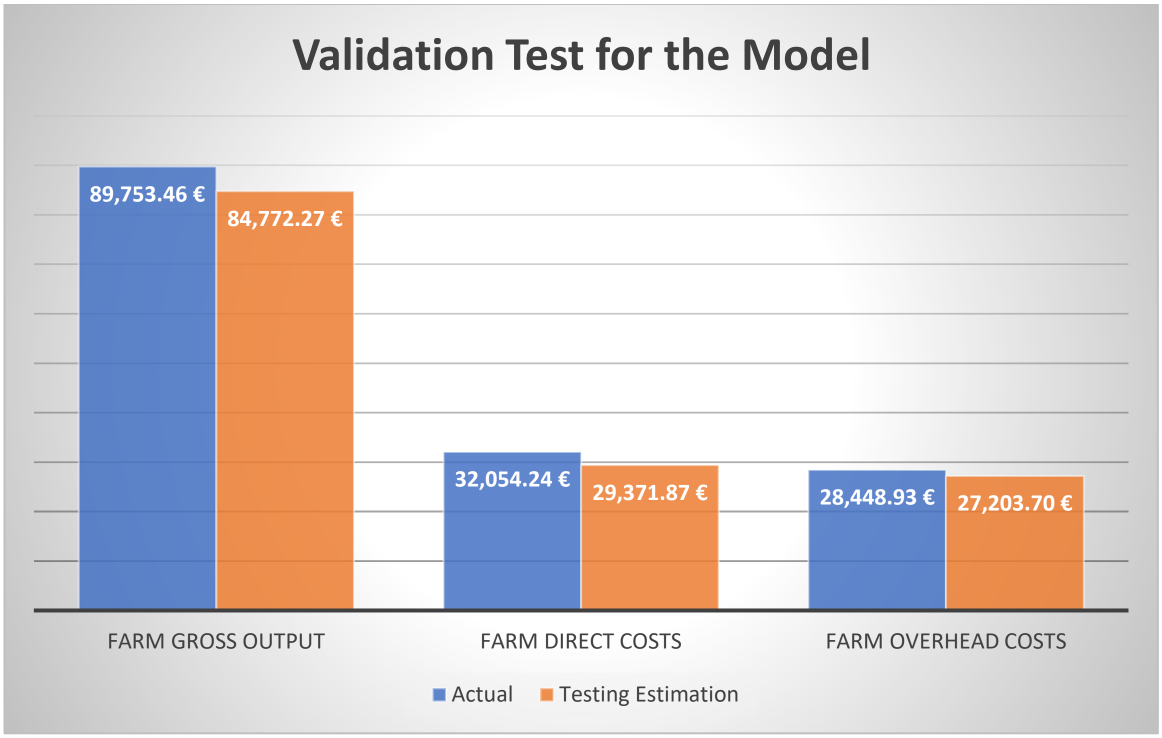

Figure 5.2. The validation of the accuracy of the Deep Learning Model

A Comparison of an Increase and Decrease in Investments

Table 5.5 presents a comparison of the actual farm gross output values from Deep Neural Networks with values after a 10% increase and 10% decrease in investments in machinery, livestock, and buildings. The table includes information on counts, means, standard deviations, minimum and maximum percentiles, as well as quartiles (25th, 50th, and 75th percentiles).

After a 10% increase in investments, farm gross output showed an increase of 12.85%, 9.28%, and 1.83% in the 25th, 50th, and 75th percentiles of the farm gross output range, respectively. However, for the top quartile (75% to 100%) of the farm gross output range, the gross output decreased significantly by 61.42%.

Conversely, after a 10% decrease in investments, farm gross output also declined by 3.30%, 6.19%, 12.69%, and 65.85% in the bottom first to fourth quartiles of the farm gross output range. The mean impact of a 10% increase in investments on farm gross output was 1.35%, while a 10% decrease led to a substantial decrease of -13.14% in farm gross output.

Table 5.5. Actual farm gross output comparison with 10% increased and 10% decreased values (€)

	Actual Farm Gross Output	10% Increased Farm Gross Output	Percentage Change (%) of Increase	10% Decreased Farm Gross Output	Percentage Change (%) of Decrease
count	24611	24611		24611	
mean	89493.94	90699.47	1.35%	77738.32	-13.14%
std	99424.31	91503.90	-7.97%	78472.32	-21.07%
min	0.00	2.25		2.30	
25%	27058.53	30536.14	12.85%	26166.65	-3.30%
50%	56362.13	61591.29	9.28%	52872.50	-6.19%
75%	116447.50	118573.90	1.83%	101669.40	-12.69%
max	3339889.00	1288400.00	-61.42%	1140662.00	-65.85%

Table 5.6 provides a comparison of the actual farm direct costs values with values after a 10% increase and 10% decrease in investments in machinery, livestock, and buildings. The table

presents counts, means, standard deviations, minimum and maximum percentiles, as well as quartiles (25th, 50th, and 75th percentiles). Following a 10% increase in investments, farm direct costs saw an increase of 47.85%, 27.34%, and 10.67% in the 25th, 50th, and 75th percentiles of the farm direct costs range, respectively. However, for the top 75% to 100% range of farm direct costs, a 10% increase in investments resulted in a substantial decrease of 78.28% in direct costs.

Conversely, after a 10% decrease in investments, farm direct costs also decreased by 6.06%, 18.49%, and 82.81% in the second to fourth quartiles of the farm direct costs range. Surprisingly, the bottom 25% farm direct costs percentile increased by 9.07% after a 10% decrease in investments. The average effect of a 10% increase in investments on farm direct costs was 7.49%, while a 10% decrease led to a significant decrease of -20.71% in farm direct costs.

Table 5.6. Actual farm direct costs comparison with 10% increased and 10% decreased values (€)

	Actual Farm Direct Costs	10% Increased Farm Direct Costs	Percentage Change (%) of Increase	10% Decreased Farm Direct Costs	Percentage Change (%) of Decrease
count	24611	24611		24611	
mean	31983.03	34377.66	7.49%	25358.56	-20.71%
std	44263.75	34793.17	-21.40%	25764.90	-41.79%
min	0.00	-0.52		-0.04	
25%	7861.91	11624.14	47.85%	8574.72	9.07%
50%	18361.50	23381.29	27.34%	17248.71	-6.06%

75%	40575.71	44905.10	10.67%	33072.51	-18.49%
max	2676570.00	581424.19	-78.28%	460135.13	-82.81%

Table 5.7 presents a comparison of the actual and estimated values after a 10% increase or 10% decrease in investments in machinery, livestock, and buildings, focusing on the count, mean, standard deviation, minimum, 25th, 50th, 75th, and maximum farm overhead cost percentiles. With a 10% increase in investments, farm overhead costs experienced slight increases of 2.27%, 2.57%, and 3.48% in the 25th, 50th, and 75th farm overhead cost percentiles, respectively. However, for the top quartile (75% to 100%) of the farm overhead cost range, a 10% increase in investments resulted in a notable decrease of 43.96% in overhead costs. On the other hand, after a 10% decrease in investments, farm overhead costs declined by 18.32%, 18.31%, 18.19%, and 50.09% for the first to fourth farm overhead cost quartiles. The average impact of a 10% increase and 10% decrease in investment on farm overhead costs was -1.39% and -21.89%, respectively.

Table 5.7. Actual farm overhead costs comparison with 10% increased and 10% decreased values (€)

	Actual Farm Overhead Costs	10% Increased Farm Overhead Costs	Percentage Change (%) of Increase	10% Decreased Farm Overhead Costs	Percentage Change (%) of Decrease
count	24611	24611		24611	

mean	28339.65	27945.51	-1.39%	22137.36	-21.89%
std	33552.11	29592.13	-11.80%	23497.90	-29.97%
min	-9508.39	2.34		2.06	
25%	8680.80	8877.90	2.27%	7090.44	-18.32%
50%	17809.40	18266.48	2.57%	14549.37	-18.31%
75%	35295.76	36524.43	3.48%	28875.99	-18.19%
max	672717.00	376962.72	-43.96%	335757.00	-50.09%

Figure 5.3 illustrates the change in farm gross output after a 10% increase or a 10% decrease in investments in machinery, livestock, and buildings. Compared to the actual data with no increase or decrease, farm gross output increased across the second to eighth gross output deciles, ranging from 1.96% to 12.59%. Conversely, the first, ninth, and tenth deciles experienced a decline in farm gross output with a 10% increase in investments. On the other hand, a 10% decrease in investments resulted in a decrease in farm gross output across all ten gross output deciles, ranging from 3.46% to 20.95%.

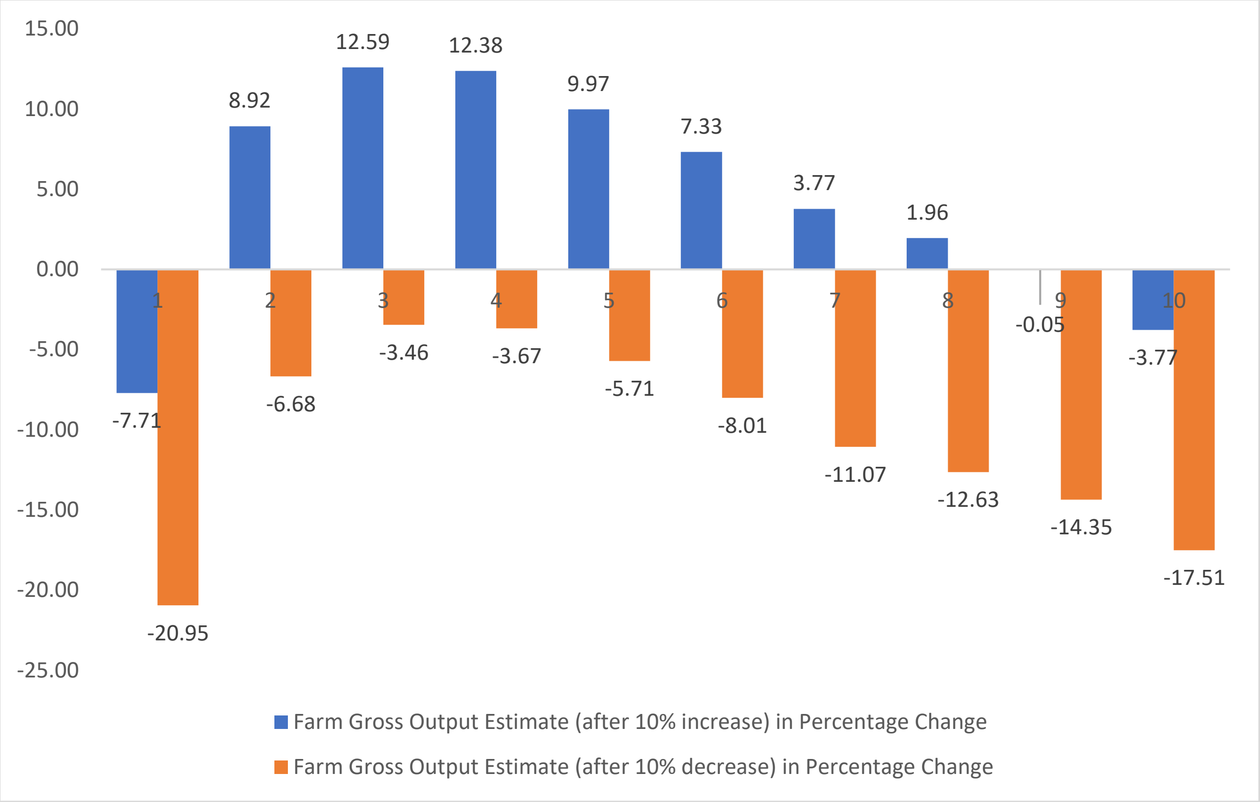

Figure 5.3. Farm gross output change after 10% increase and decrease in investments (€)

Figure 5.4 displays the change in farm direct costs after a 10% increase and a 10% decrease in investments in machinery, livestock, and buildings. Following a 10% increase in investments, farm direct costs also increased across the first to ninth direct costs deciles, ranging from 5.04% to 49.45%, compared to the actual data with no increase or decrease. However, the tenth farm direct costs decile experienced a decline of 7.55% with a 10% increase in investments. On the other hand, a 10% decrease in investments resulted in a decrease in the first and fifth to tenth farm direct costs deciles, ranging from 1.87% to 31.69%, while the second to fourth farm direct costs deciles increased.

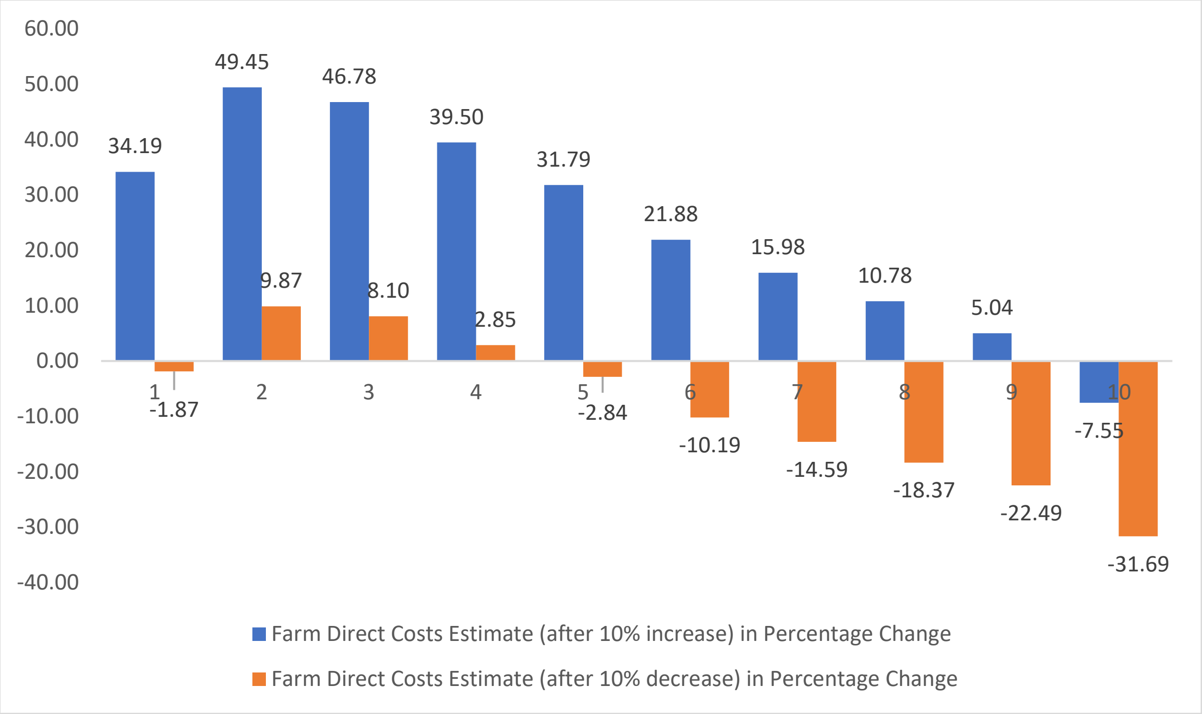

Figure 5.4. Farm direct costs change after 10% increase and decrease in investments (€)

Figure 5.5 depicts the change in farm overhead costs after a 10% increase and a 10% decrease in investments in machinery, livestock, and buildings. With a 10% increase in investments, farm overhead costs increased from the third to ninth overhead costs deciles, ranging from 1.55% to 3.32%, when compared to the actual data with no increase or decrease. However, the first (4.74%), second (0.12%), and tenth (7.36%) overhead costs deciles experienced a decline in farm overhead costs with a 10% increase in investments. On the other hand, after a 10% decrease in investments, a decrease in all ten overhead cost deciles, ranging from 18.25% to 26.65%, was observed.

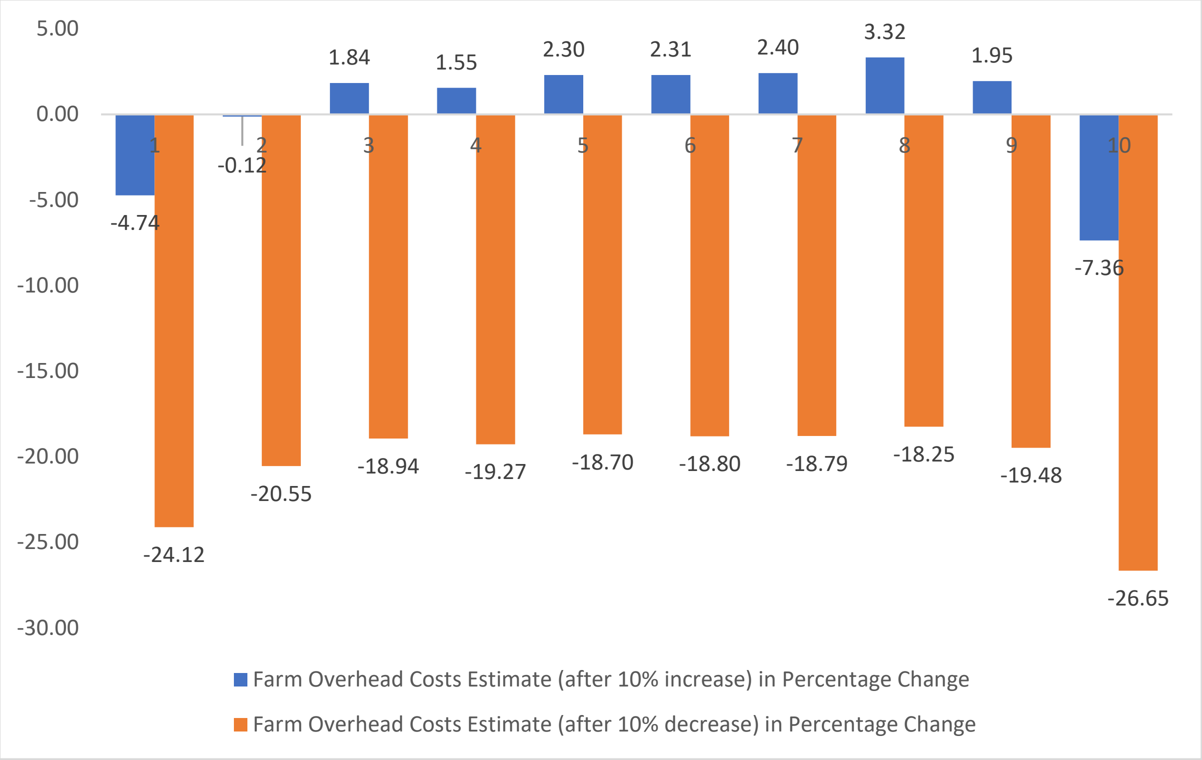

Figure 5.5. Farm overhead costs change after 10% increase and decrease in investments (€)

Relatively recent developments in the field of analytical methodologies, such as machine learning, have enabled a new and expanded analysis of the explanatory factors influencing farm gross output, farm direct costs, and farm overhead costs. These findings contribute to a deeper understanding of the role of investments in farm gross output, as well as direct and overhead costs.

5.4. Discussion

Understanding the impact of farm investments on farm gross output and costs is crucial for farmers and agricultural policymakers to maintain the economic viability of farms. Given the global importance of food security and recent increases in food prices, it has become even more critical for farmers to closely monitor output and costs while ensuring overall farm profitability. As demonstrated in this study, farm investments do influence farm output and costs, but the magnitude of this influence varies depending on the size of farm output and costs. It is also supported by a study (Kirchweger et al., 2015) that found that farm investments increase production.

It was observed that increasing investments in machinery, livestock, and buildings resulted in increased farm gross output for most gross output deciles, except for the lowest and highest gross output farms. Higher gross output increases were particularly noticeable around the third and fourth deciles. Conversely, decreasing investments led to a decrease in farm gross output across all output deciles. A related research investigated that limited investment amounts lead to elevated expenses and diminished production efficiency, culminating in an agricultural production system that lacks competitiveness (Zdeněk and Lososová, 2020).

Regarding farm direct costs, increasing investments led to an increase of more than five percent in all direct cost deciles, except for the top tenth decile. However, decreasing investments only affected certain direct cost deciles. For farm overhead costs, an investment increase in machinery, livestock, and buildings resulted in slight increases, ranging up to about three percent in overhead cost deciles, while simultaneously decreasing costs in the bottom first, second, and top tenth overhead deciles. Conversely, an investment decrease led to a decrease of approximately twenty percent in most overhead cost deciles. Another study found that substantial spending on investments, often backed by loans, leads to heightened expenses. However, study's every farm category that undertook these investments witnessed an improvement in the cost-effectiveness of specific inputs (Czubak et al., 2021). Mogues et al. (2015) mention that governmental financial measures, like subsidies or taxes, are frequently employed to incentivize alterations in production behavior by modifying the production cost or the revenue and profit derived from production encountered by the individual or entity involved. The new findings of this paper provide valuable insights for farmers and farm decision-makers in better understanding and managing agricultural investment factors related to farm gross output and costs. Findings also show that based on the size of farm output and costs farms will respond differently to investments.

5.5. Conclusion

The performance of farm enterprises is substantially influenced by agricultural output and costs, and extensively examined by scholars using diverse methods and data. Yet, an overlooked area in current literature pertains to the potential impacts of altering investments on farm output and costs. This paper seeks to bridge this gap by exploring the consequences of fluctuating farm investments, aiming to provide insight into their implications.

Previous literature studies often used linear models to scrutinize farm output and costs, lacking inherent validation testing. In contrast, our research employs a relatively innovative deep learning technique to examine how investment variables—such as machinery, livestock, and buildings—affect farm gross output, direct costs, and overhead costs. This approach yields fresh insights into the literature of agricultural output, costs, and farm investments.

Understanding the factors that impact farm income due to investments holds immense importance for farmers aiming to optimize profits and manage expenses. Farm profit, derived from the disparity between farm output and costs, hinges on these factors. Familiarity with these influential elements can serve as a valuable tool for farmers and agricultural policymakers when making informed decisions.

The findings demonstrate the impact of altering investments in machinery, livestock, and buildings on farm gross output, direct costs, and overhead costs. A 10% increase in investments led to increased farm gross output across mid-range deciles, while the highest and lowest deciles saw decreased output. Meanwhile, a 10% decrease in investments resulted in decreased farm gross output across all deciles.

Following a 10% increase in investments, farm direct costs increased across most cost deciles but decreased in the highest cost decile. Conversely, a 10% decrease in investments led to decreased costs in most deciles with increases in the mid-range deciles. Regarding overhead costs, a 10% increase in investments led to increased costs in several mid-range deciles, but decreased costs in the highest, lowest, and second deciles. Conversely, a 10% decrease in investments resulted in decreased overhead costs across all deciles.

Future research could explore the nuanced impact of varying investment distribution among machinery, livestock, and buildings on farm output and costs. Examining the interaction effects between different types of investments and their influence on specific sectors of agricultural production could provide a more comprehensive understanding of optimizing investment strategies.

Additionally, investigating the long-term implications of investment changes on farm sustainability and economic resilience could be beneficial. Understanding how these changes affect ecological sustainability, resource management, and the adaptive capacity of farms in different regions or contexts would offer valuable insights for sustainable agricultural practices.

Finally, exploring the potential role of government policies or incentives, such is farm subsidies, in influencing investment decisions and their subsequent effects on farm output, costs, and overall agricultural systems could be an area of interest for future research. Understanding how policy interventions can support or hinder investment dynamics within the agricultural sector would be beneficial for policymakers and stakeholders aiming to optimize farm performance and long-term sustainability.

Authors Contribution

Dilovar Haydarov – Writing the paper and doing the analysis

Chaosheng Zhang – Minor Revision

Data Availability

To access the data used to support the findings of this study, Teagasc - the Agriculture and Food Development Authority should be contacted at https://www.teagasc.ie/rural-economy/rural-economy/national-farm-survey/.

Declaration of Competing Interest

The authors declared no conflict of interests.

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6. CHAPTER SIX: A spatial analysis of farmers' intentions to adopt nutrient management practices – a case study of soil pH management in Ireland

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Abstract

While research studies have examined individual aspects of the adoption of natural resource use optimization practices to underpin the sustainable intensification of agricultural production to feed growing populations, there is a dearth of literature that takes a holistic view of how factors such as farm and farmer demographics, behavioral drivers, cost-benefit drivers analysis, and the agronomic necessity to implement nutrient management practices may vary depending on the environmental contexts of individual farms. This research aims to investigate whether there is a positive correlation between the need to lime and the intention to lime, or if they surprisingly oppose each other. Furthermore, the study will examine the factors that drive this association, focusing on the Republic of Ireland as a case study country. The research draws on data from sources such as a national farm behavioural survey of nutrient management planning practices, the annual Teagasc National Farm Survey, a spatial dataset of Irish farms including environmental data, and a pH map of Irish soils Soil Geochemical Atlas. Employing the Theory of Planned Behavior as its framework, the study primarily uses statistical matching techniques. It also employs ordinary least squares, logistic, and geographically weighted regressions for analysis. Findings show that, on average, there's a 79% probability that a farmer recognizing the need to lime, due to low soil pH, will indeed intend to lime. The study identifies perceived behavioral controls, subjective norms, and perceived resources as positive influencers on farmers' intentions to apply lime. Surprisingly, farmers' attitudes are negatively linked to their intention to lime. Interestingly, higher formal education levels, such as college degrees or professional diplomas, significantly boost farmers' inclination to apply lime. Age categories indicate an inverse relationship between age and farmers' intention to implement lime nutrient management practices. This study illuminates the multifaceted dynamics of behavioral factors influencing farmers' decisions regarding lime management practices and the role played by geospatial environmental dimensions in this interaction. The paper's findings offer agricultural managers and policymakers valuable information that assists in shaping their decisions and approaches toward agricultural management.

Keywords: Farm modelling, spatial modelling, environmental management, theory of planned behaviour, nutrient management

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6.1. Introduction

The world population is predicted to increase to 9.8 billion by 2050 (U.N. DESA, 2017). To meet the increased demand for food due to this population growth, the agricultural sector must enhance its efficiency in utilising agricultural land and sustainably increase output per hectare. For pastoral based livestock-farming systems, the effective use of nutrient management practices is crucial in achieving optimal output per hectare (Daxini et al., 2018; Goulding et al., 2008). However, it is important to note that the necessity to adopt the best nutrient management practices may not necessarily align with farmers' behaviours or their intention to adopt such practices (Daxini et al., 2019). An additional confounding factor is that the cost of impelementation and effectiveness of nutrient management practices are determined largely by spatial factors such as soil type and soil alkalinity. For this reason, this paper addresses how adoption behaviour of nutrient management plans can interact with farm characteristics and spatial factors and how this information can in turn influence farmers, intermediaries and policy makers across the agricultural sector.

Nutrient Management Planning (NMP) is a proven farm productivity tool that enables farmers to increase productivity by optimising the organic nutrients in manure produced by livestock (Osmond et al., 2015; Ulrich-Schad et al., 2017), while also reducing the application of on expensive (inorganic) chemical fertilisers (Sharpley et al., 2003). A key underlying factor is the optimisation of soil pH through the application of lime to increase soil alkalinity, thus allowing for more efficient uptake of both organic and chemical nutrients, with associated economic benefits (Wall and Plunkett, 2016). However, research shows that despite the obvious advantages, uptake of NMP is often lower than expected (Osmond et al., 2015; Collins et al., 2016). There are a number of reasons put forward for poor adoption of NMP practices. NMP is a complex process, requiring considerable knowledge and training (Micha et al., 2018), thus individual farmer characteristics and farm management behaviour can be a factor (Nuthall and Old, 2018). There is also a spatial dimension as NMP components such as increasing soil alkalinity (pH) to optimise the utilisation of soil nutrient uptake is dependent on local soil conditions, therefore the need for lime application to increase soil pH varies spatially. The economic benefits of NMP have recently come into focus with the increase in fertiliser costs and the supply chain issues resulting from the Ukraine war. However, there appears to be little or no literature that combines the examination of all of these factors. This paper is thus timely and unique as it undertakes an integrated analysis of the interaction of the behavioural, spatial and economic aspects of the adoption of NMP measures.

The economic returns of farms are influenced by behavioral drivers, such as the intention to adopt nutrient management practices, and these factors have a spatial dimension. This study adopts the theory of planned behavior (Ajzen, 1991; Madden et al., 1992) as a theoretical framework to explain farmers' intention to apply nutrient management practices. According to Ajzen's theory, intention or behavioral intention is shaped by attitudes, subjective norms, and perceived behavioral controls, ultimately determining whether a person takes specific actions. An extension to this theory includes perceived resources, which considers available financial or labour resources that also influence farmers' intentions to optimise the fertility and nutrient optimization fo their farms (Daxini et al., 2018).

Previous research has explored the impact of various factors on farmers' intentions to adopt nutrient management planning. However, few studies incorporate the spatial dimension or consider the cost-benefit relationship of nutrient management practices. For instance, Daxini et al. (2019) studied the influencing elements of farmers' intentions to follow nutrient management planning but did not account for the spatial dimension and cost-benefit factors. Similarly, Ulrich-Schad et al. (2017) analysed factors influencing low nutrient management practice uptake among farmers but did not consider geographical and cost-benefit factors. Savari and Gharechaee (2020) investigated behavioral variables influencing farmers' intentions to use chemical fertilizers safely but did not study the spatial interaction of behavioral factors, nor did they include economic elements like financial gain or expenditure on nutrient management practice.

On the other hand, Nissen et al. (2003) focused on the economic aspect of nutrient management planning, particularly the financial yield of macronutrients and lime application, and also analyzed the spatial variability of farm size for profitable fertilizer spreading. However, their model did not consider behavioral elements that could also influence nutrient application practices and economic returns. Similarly, Tufenkci et al. (2006) explored the effect of nutrient application on plant growth and yield but did not take into account spatial or behavioral factors in their study.

This paper aims to fill a gap in the literature by establishing a relationship and dependence between behavioral drivers, economic returns, and the spatial dimension of nutrient management practices. The study is predicated on spatial soil heterogeneity and how the need to balance soil pH level differs spatially across farms. It addresses three main aspects: first, whether behavioral factors impact farmers' intentions to implement lime recommendations; second, whether there is a correlation between farmers' intention to apply lime and various farm-related characteristics, such as output, cost, temperature, and rainfall; third, an analysis of the cost and benefit of liming, including the spatial dimension of the economic return from liming. Additionally, the study examines the hypothesis of whether the need to lime is supported or correlated with the intention to lime.

Using the Republic of Ireland as a case study country that relies on outdoor farming systems, particularly dairy, cattle, sheep, and tillage, the research analyses these farming systems by considering the influence of spatial environmental factors, nutrient management measures, and farmers' behaviors on grass/crop growth and yield. One of the challenges in conducting this research is the lack of a single dataset that includes behavioral, economic, and spatial information. To address this issue, the paper employs a statistical matching technique to combine multiple datasets, each containing different elements of the information necessary for the study. The statistical matching technique uses the Mahalanobis distance equation, as explained in Decoster et al. (2014), to match and combine behavioral, economic, and spatial datasets effectively.

The organisation of this paper is as follows: Section 2 delves into the theoretical framework, covering soil health, soil fertility, the cost and return of liming to increase soil pH, and focusing on the behavioural drivers of a key nutrient management practice, namely the adoption of liming. In Section 3, the methodological choices, including the use of statistical matching, are explained, and the data utilized in the study is presented. Moving on to Section 5, the findings and results of the analysis are discussed. The concluding Section 5 highlights the potential applications of the paper's methodology and findings, particularly in designing spatially targeted policies and assessing ex-ante impacts of policies in various spatial contexts.

6.2. Theoretical Background

This section focuses on three elements of the theoretical framework and their interconnection. It begins by elaborating on soil fertility and its influence on grass output productivity. Next, the cost and benefits of lime application, particularly in achieving a stabilized soil pH level, are discussed. Subsequently, the behavior-related aspects of lime application, analyzed within the context of the theory of planned behavior, are examined. These frameworks are subjected to testing later on, and the findings derived from them are presented in the results section.

6.2.1. Soil Fertility and Lime as a part of Nutrient Management Planning

Agricultural productivity is influenced by the inherent characteristics of agricultural soils, which can be improved by applying nutrients in the form of chemical fertilizers or animal manure. However, soil and climatic conditions vary across different regions, which necessitates the practice of tailored Nutrient Management Planning (NMP) on a farm-by-farm (and even field-by-field) basis. NMP involves matching the nutrient needs of soils to their specific environmental context, ensuring that the right amount of nutrients is applied for optimal crop growth. This approach focuses on applying the correct nutrients in the right locations and at the right time, leading to two important outcomes: (a) farmers can achieve optimal yields from their soils, and (b) farmers avoid excessive application of nutrients, which can be costly for both the farmer and the environment due to potential emissions to air and water.

A crucial step in NMP is conducting a soil test to determine the soil's alkalinity level, measured as pH. The optimal soil pH is 6.7, and soils with pH levels below this range require lime application to increase the pH and improve the soil's capacity to utilize essential elements like phosphorus (P) and nitrogen (N). If the pH is not close to the optimal range, the uptake of P fertilizers becomes sub-optimal, resulting in reduced efficiency in the utilization of N fertilizers, and increased nitrogen emission (McNicol et al., 2024). If the required amount of lime is not applied as part of a NMP program, the overall effectivenss of NMP as a management and productivity tool is diminished, and/or money spent on other NMP practices may not be wasted (Wall and Plunkett, 2016).

Indoor farming systems rely on purchased animal fodder, such as concentrate feeds and hay, while outdoor farming systems mainly feed their livestock with grass from their farmlands. Outdoor farming systems are particularly sensitive to environmental conditions, such as extreme temperatures or inadequate or high levels of rainfall, which can limit grass growth. In such cases, farmers may be forced to buy animal foodstuffs to supplement their reduced grass production.

For outdoor farming, grass growth depends on maintaining fertile soil, where adequate pH levels and essential macronutrients like nitrogen, phosphorus, and potassium are pivotal. Farmers are advised to regularly assess soil fertility, adjusting lime and macronutrient levels within recommended ranges, typically between 6.3 to 7.0 pH, as advised by agricultural authorities like Teagasc (Irish Agriculture and Food Authority) in Ireland. When soil pH strays from this optimal range, macronutrient absorption by grass diminishes, leading to wastage and potential environmental pollution as excess nutrients get washed away.

Efficient macronutrient uptake by grass necessitates maintaining soil pH within the optimal range. Applying lime, such as calcium carbonate (CaCO3), serves as a common method to stabilize soil pH. This approach helps balance and regulate pH levels, aiding in better nutrient absorption. Soil fertility tests guide farmers on lime application rates and frequency, crucial steps in ensuring effective nutrient uptake for sustained grass productivity while minimizing environmental impact.

6.2.2. Cost and Benefit of Liming

When farmers are deciding whether to apply lime or not, they assess whether the advantages of liming outweigh the associated costs. If farmers perceive that the benefits they will gain from liming exceed the expenses incurred for lime application, it motivates them to adopt liming as part of NMP. To demonstrate the economic spatial returns of using lime in different biophysical contexts, this paper calculates the spatial distribution of costs and benefits. Considering the spatial dimension of the economics of lime application enables farmers, farm advisors, and policymakers to develop and evaluate their planning, advice and policies more effectively.

Here we define the profit function as the net benefit of applying lime, which is the total benefit of lime application less total cost of liming:

$$NB_{i,j} = TB_{i,j} - TC_{i,j} \tag{1}$$

where $NB_{i,j}$ refers to the net benefit of applying lime per farm (i) and per hectare (j) or per livestock unit (j). $TB_{i,j}$ is the total benefit of liming and $TC_{i,j}$ is the total cost of it. In the results section, the estimation of the net benefit of applying lime will be given per hectare and not per livestock unit. It is because the lime benefit is directly related to much much land a farm has.

The total benefit of lime application corresponds to the monetary amount (in €) saved on fertilizers/macronutrients, which would otherwise be wasted due to the farmland's suboptimal pH level. In simpler terms, the lower or suboptimal the soil pH level of a farm, the greater the amount of fertilizers/macronutrients that will be wasted, as grass has a lower absorption rate under such conditions. This wasted amount is considered the total benefit if the farm had an optimal pH level. Therefore, if a farm's soil pH level falls within the optimal range, the total economic benefit of liming for that farm will be zero. It is with an assumption that no amount of fertilizers will be wasted as long as the farmer follows the recommended nutrient management advice and applies the required quantity of macronutrients.

On the other hand, the total cost of lime application is calculated as the combined cost of acquiring the required amount of lime and applying it to raise the farmland's soil pH from below the optimal range to the optimal range. For example, a farm with a suboptimal pH level of 4.5 will have a higher total cost of lime application compared to another farm with a pH level slightly below the optimal range, say 5.5. This cost includes both the expense of purchasing lime and the spreading fee. As of 2019, the commonly used ground limestone in Ireland (calcium carbonate) generally costs around €25 per tonne, covering both the cost of lime itself and the spreading fee (Fertilizer Association of Ireland, 2016).

6.2.3. Behavioural Drivers - Theory of Planned Behaviour

When it comes to nutrient management practices, farmers' decision-making is influenced by their beliefs and behavioral psychology (Daxini et al., 2018). Their psychological behavior plays a crucial role in determining whether they will follow lime management advice. If farmers have a negative behavioral intention towards applying lime, they may choose to reject the advice even if it is necessary. Therefore, in order to understand the behavioral aspect of lime nutrient management practices among farmers, this paper needs to select and use a theoretical framework from behavioral psychology.

In the field of psychology, there are several theoretical frameworks related to behavior and beliefs. One such framework is the Theory of Reasoned Action (Fischbein and Ajzen, 1975), which explains the connection between behaviors and attitudes. However, this theory has faced criticism for not accounting for certain situations that may not be accessible to certain individuals. Despite this criticism, proponents argue that these unaccounted factors are still part of the framework and should influence individuals' intentions (Eagly and Chaiken, 1993).

Another theoretical framework in the behavioral field is the Fogg Behavior Model (Fogg, 2009). This model proposes that an individual's behavior is influenced by their ability, motivation, and triggers. Motivation includes psychological conditions such as pleasure, pain, and hope, while ability includes factors like time, money, and physical effort. Triggers serve as reminders of a person's behavior, with examples being text messages or alarms. While this model can be used by psychological practitioners to achieve specific behavioral goals, it lacks a broader scope of influential factors on behavioral intention, such as group/customary norms and behavioral attitudes.

The Theory of Planned Behavior (TPB) is another theoretical framework from behavioral psychology, which seeks to assess factors influencing behavioral intention (Ajzen, 1985; Ajzen, 1991). The components of this theory are attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991; De Leeuw et al., 2015). These components, in turn, influence behavioral intention, which guides a subject to actually carry out a given action or task. The formula for this theory is as follows (Ajzen, 1991):

$$BI_i = w_A A_i + w_{SN} SN_i + w_{PBC} PBC_i \tag{2}$$

where BI_i represents the behavioural intention, A_i attitudes, SN_i subjective norms and PBC_i perceived behavioural control; w_A, w_{SN} and w_{PBC} are the statistical coefficients or weights.

Each component or predictor of behavioral intention in the TPB corresponds to different psychological constructs. Attitudes represent the level of favorable or unfavorable evaluation of a particular behavior or action. Subjective norms refer to beliefs about the approval or disapproval of a certain behavior or action by the majority in a given region, for example, local peers. Perceived behavioral control defines the perceived difficulty or ease of performing a specific action or behavior by an individual.

There are several reasons for choosing the theory of planned behavior as the behavioral framework for this paper. Firstly, this theoretical framework has been extensively researched and widely used in various contexts. Secondly, it encompasses comprehensive and clearly defined elements of beliefs and behaviors. Additionally, it aligns well with the context of lime application recommendations and has already been utilized by Daxini et al. (2018) to assess behavioral intention related to nutrient management practices in general.

An extension to the original theory of planned behavior, this study incorporates ‘perceived resources’ as the fourth predictor/component to explain behavioral intention to apply lime. This addition is based on the work of Zeweld et al. (2017), where perceived resources are defined as the level of access to technical infrastructure, time, finance and labor resources necessary to carry out lime nutrient management practices. The inclusion of the perceived resources component in the framework is important as it serves as a predictor of behavioral intention. Possessing or having access to the required resources, whether technical or financial, impacts whether farmers have a positive or negative intention to follow lime application recommendations.

6.2.4. Linking the Soil Health, Economic Benefit and Behavioural Drivers of Lime Application

The combination of the three frameworks (soil health, cost-benefit of liming, and behavioral drivers of lime application) along with the spatial dimension forms a holistic theoretical framework. Based on the soil health conditions, the following hypotheses will be tested; What are the behavioral factors that impact farmers' intention to apply lime? How do farm-related characteristics such as farm output, rainfall and physical farm characteristics influence farmers' intentions? What is the economic cost-benefit of liming, and is there a net benefit to individual farmers? Are the regions where farmers need to apply lime also the regions with relatively higher intention to apply lime?

When analysing behavioral factors, attitudes, perceived behavioral control, subjective norms, and perceived resources will serve as explanatory variables for farmers' intention to follow lime recommendations and apply them. Additionall, farm systems, farm size, farm family income, age, educational level, gender, support of agricultural advisor, low pH level (need to apply lime), and soil categories will be used as independent variables. Estimating the cost and benefit of liming aims to determine if an economic incentive exists and to provide rational motivation for following lime advice. Finally, the paper will examine whether the need to stabilize pH levels (independent variable) through liming is correlated with farmers' intention (dependent variable) to lime.

6.3. Data and Methodology

The paper's analysis will utilise the following datasets. Firstly, the farm variables from the Teagasc National Farm Survey will be matched with datasets from the nutrient management planning survey developed by Daxini (2018). The nutrient management planning survey has behavioral variables. Then, the matched datasets will be merged with spatial data. The spatial data is a data extract of the SMILE (Simulation Model of the Irish Local Economy) model (O’Donoghue et al. 2017). The SMILE data is the key data that links a farm’s characteristics with its geospatial farm attributes. The SMILE data is explained in detail later in the section. Finally, pH data, which is explained in the sub-section 3.3., will be linked into the overall data framework. The subsections below provide detailed explanations for each data source.

In the methodology section, the paper first describes the statistical matching technique used. Secondly, it explains the development of a microsimulation spatial model that will be used to incorporate the spatial variables. Lastly, the paper outlines the estimation steps for calculating the cost and benefit of liming practices.

6.3.1. National Farm Survey

The primary data source for the model is the Teagasc National Farm Survey (NFS), which was collected from 2001 to 2014 This survey selects approximately 1000 farms each year based on

Central Statistics Office quotas, with assigned weights to ensure national representativeness of the Irish farm population (Teagasc, 2023). The NFS is part of the EU's Farm Accountancy Data Network (FADN) and is utilized for policy, research, financial, and performance measurement purposes.

The survey gathers a range of variables, including costs, subsidies, purchases, assets, liabilities, yields, inventories, and sales. Farms in the survey are categorized into dairy, cattle rearing, cattle other, sheep, and tillage systems. However, poultry and pig systems are not well-represented in the Teagasc NFS due to their small number.

In the paper's analysis, NFS variables from Table 6.1 will be used for statistical matching with variables from the nutrient management planning survey in Table 6.2. Specifically, farm codes from the Teagasc National Farm Survey will be matched with the SMILE data (explained in sub-section 3.5). The variables listed in Table 6.1 are the ones used for the analysis. The first soil group includes soil classes 1 and 2, representing good soils with a wide range of uses. The second soil group encompasses classes 3 and 4, representing an average soil type with a somewhat limited use range. The third soil category represents relatively poorer soils with very limited use range.

Table 6.1. Teagasc National Farm Survey Variables (2001-2014)

Variable	Obs	Mean	Std. Dev.	Min	Max
Farmers Age	122889	54.28	13.21	0.00	86.00
Total Land Farmed (ha)	122889	3.43	1.05	1.00	5.00
Farm Family Income	122889	3.89	2.18	1.00	7.00
Mainly cattle	122889	0.41	0.49	0.00	1.00
Mainly dairying	122889	0.37	0.48	0.00	1.00
Mainly sheep	122889	0.14	0.35	0.00	1.00

Mainly tillage	122889	0.08	0.27	0.00	1.00
Soil Group 1 (Classes 1 and 2)	122889	0.55	0.50	0.00	1.00
Soil Group 2 (Classes 3 and 4)	122889	0.36	0.48	0.00	1.00
Soil Group 3 (Classes 5 and 6)	122889	0.08	0.28	0.00	1.00
Farmer Gender (male)	122889	0.97	0.18	0.00	1.00
Farmer Gender (female)	122889	0.03	0.18	0.00	1.00

6.3.2. Nutrient Management Survey

A face-to-face nutrient management survey was conducted in 2017 by a private survey company, where a total of 1009 Irish farms were surveyed. The questionnaire collected information relating to farm activities for the year 2016 and consisted of 79 questions, with the first 12 questions focusing on farm characteristics. The farm systems represented in the survey were dairy, cattle, sheep, and tillage, with demographic questions (e.g., size, system) and farmers' characteristics (e.g., age, education and interaction with an agricultural advisor). The second part of the survey focused on gathering data about farmers' motives behind embracing particular NMP practices, including a section on liming. The last section centered on the Theory of Planned Behavior (TPB), where farmers were prompted to assess various statements structured to unveil their beliefs and intentions concerning the application of NMP practices.

Table 6.2 provides summary statistics of the 2017 nutrient management survey variables that are utilized in this paper for statistical matching with the Teagasc National Farm Survey variables. The aim is to link the attitudinal variables related to nutrient management planning with the farm codes from the National Farm Survey. This matching process using the Mahalanobis distance (explained in the sub-section 3.6) creates a dataset that includes both attitudinal and behavioral variables, which is later linked with spatial attributes and information.

Table 6.2. 2017 National behavioural survey of intentions to adopt NMP practices: Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Total land farmed in hectare	1009	2.78	1.22	1.00	5.00
Age	1009	55.49	13.49	18.00	91.00
Income band	1009	4.57	2.68	1.00	8.00
Mainly cattle	1009	0.51	0.50	0.00	1.00
Mainly dairying	1009	0.26	0.44	0.00	1.00
Mainly sheep	1009	0.17	0.37	0.00	1.00
Mainly tillage	1009	0.06	0.24	0.00	1.00
Good, wide use soil	1009	0.75	0.43	0.00	1.00
Average, somewhat limited use range soil	1009	0.23	0.42	0.00	1.00
Poor, very limited use range soil	1009	0.01	0.12	0.00	1.00
Gender (male)	1009	0.93	0.25	0.00	1.00
Gender (female)	1009	0.07	0.25	0.00	1.00
Tillage land (hectares_	1009	0.00	1.00	-0.23	24.30
Livestock unit per hectare of farm area	1009	0.00	1.00	-0.86	9.29
Rented land (ha)	1009	0.00	1.00	-0.21	27.95

6.3.3. Identifying the need for lime application – soil pH data

Soil pH (potential of hydrogen) is an important factor that defines the uptake level of nutrients needed by the soil. Soil alkalinity is meausured using a pH scale where the optimal pH for grass/crop growth is 6.3 – 6.5[11] . Where soil is acidic or low in alkalinity, the application of lime

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[11] https://www.teagasc.ie/crops/soil--soil-fertility/soil-ph--liming/

increases and stabilizes the pH level of the soil, making lime application recommendations a crucial part of many nutrient management plans for farmers. The pH data used in this paper is sourced from the Teagasc sampled soil geochemical atlas of Ireland dataset with revisions made in 2013 (Fay et al., 2011). The collected soil samples are nationally representative of Ireland. The paper takes the raw soil samples and interpolates it by deploying the Kriging method. The interpolated soil pH values are then linked to the SMILE data based on location.

Figure 6.1 displays the spatial distribution of interpolated (estimated) pH levels using the Kriging technique across the State. It shows that the northern and west-southern regions have lower, more acidic pH levels, while the East and South-East of the country have higher, more balanced pH levels. The interpolated pH data is geographically matched with the SMILE microsimulation data described below, which contains farm IDs linked to the Teagasc National Farm Survey.

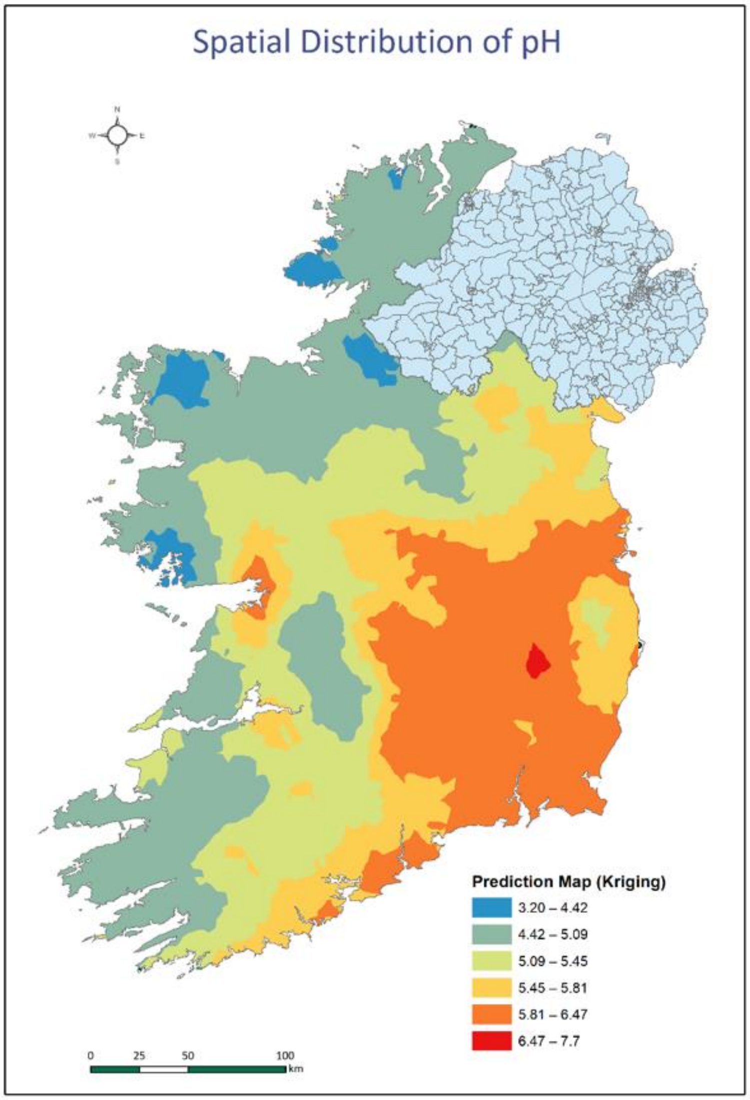

Figure 6.1. Spatial Distribution of pH in Ireland

Notes: Produced by Authors based on raw data from Fay et al. (2011).

The Kriging technique was used to interpolate the map. GIS boundary data is from Central Statistics Office (2011) and Open Data Portal for Northern Ireland (2012).

Notes; Produced by Authors based on raw data from Fay et al. (2011). by Kriging technique). GIS boundary data from Central Statistics Office (2011) and Open Data Portal for Northern Ireland (2012)).

6.3.4. Summary Statistics of Variables

Table 6.3 presents the raw variables utilised in the analysis of the paper. The behavioural variables Intention, Attitude, Perceived Behavioral Controls (PBC), Subjective Norms (SN), and Perceived Resources (PR) are employed in the geographically weighted regression, and also used later in logistics regressions. These two regressions are used to analyse farmers' intentions to undertake liming. The number of observations show the number of farms in Ireland, while mean, min and max values represent the average, minimum and maximum values for the components of TPB, townland pH, and net benefit. The behavioral variables are taken directly from the national nutrient management planning survey, while the pH variable is taken from authors' interpolated pH values. These variables represent the components of the Theory of Planned Behavior (TPB). The net benefit per hectare (per ha of utilised agricultural area) represents the total benefit achieved after lime application and stabiliing the pH level. The pH level (pH) in this context indicates the level of acidity (low pH) or alkalinity (high pH) of soils.

Table 6.3. Summary Statistics of Utilised Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Attitude	122889	4.08	0.48	1	5
PBC	122889	4.15	0.55	2	5
SN	122889	3.94	0.60	2	5

PR	122889	3.93	0.50	2	5
Intention	122889	3.79	0.93	1	5
Townland pH	122889	5.29	0.49	4.23	6.57
Net Benefit	122889	84.94	134.80	0	3226.57

The table indicates that the mean net benefit value of the group with intention to adopt is lower than that of the group with greater levels of intention. This suggests that farmers with low intentions to lime their farmlands will experience a slightly lower return (approximately €3.5/ha) compared to farmers with medium or high intention. Additionally, the table shows that low intention farmers generally have lower farmland soil pH levels compared to those with medium and high intention. Furthermore, it reveals that farmers with low pH levels will, on average, have approximately €30/ha more return than those with medium and high pH if they choose to apply lime and follow liming practices.

6.3.5. The Simulation Model of the Irish Local Economy (SMILE) Spatial Data

The Simulation Model of the Irish Local Economy (SMILE) data, as presented in the works of O'Donoghue et al. (2013 & 2017), serves as a spatial methodology that connects statistically matched datasets with farm codes. The SMILE data, generated by the SMILE model, has been extensively utilised in simulating income distributions (Morrissey and O'Donoghue, 2011; O'Donoghue et al., 2013), estimating variations in household income (O'Donoghue et al., 2012), conducting network analysis of forests (Cullinan et al., 2008), and other studies.

The SMILE model's primary purpose is to assess the socio-economic impacts of economic and policy changes. The decision to employ SMILE data in this analysis is motivated by its use of the

NFS data, representing approximately 139,000 Irish farmers, and its track record as a reliable source of microsimulation output data, proven through numerous publications across various research fields. O’Donoghue et al. (2013) detail the construction and calibration of the SMILE model, while O’Donoghue et al. (2017) explain its further development, including the creation of a base population using Census of Agriculture data and the allocation of specific characteristics to each farm in the dataset using spatial microsimulation techniques.

6.3.6. Statistical Matching

To combine multiple datasets with distinct useful information that are not available in a single database, researchers often match or link these datasets using common/similar variables present in both/all datasets. In this paper's case, the nutrient management planning dataset, containing behavioral information, needs to be matched/linked with the Teagasc National Farm Survey dataset, which provides the necessary information for estimating the cost and benefit of liming. The Teagasc national farm survey dataset, in turn, is georeferenced with the SMILE data, which includes spatial/coordinate attributes.

One widely used and tested method for this purpose is statistical matching. Early works by Rodgers (1984) utilized a distance function developed by Radner et al. (1980) to statistically match two survey datasets with household characteristic variables, such as the number of adults and children, total income estimate, and home ownership. D'Orazio et al. (2006) explored the statistical matching of categorical variables and proposed the use of logical constraints to reduce uncertainty in dataset matching.

Schleicher et al. (2020) provided guidance for statistical matching in the context of conversation impact evaluation. They emphasized the need for a clear, well-developed theory, appropriately selected covariates and matching approaches, as well as a series of checks to evaluate the quality of the match. While there are several statistical matching techniques available in the literature, the one that best suits this paper's needs is the technique developed by Decoster et al. (2007). This method employs an implicit approach, reducing reliance on theoretical assumptions, and utilizes the Mahalanobis distance equation (De Maesschalck et al., 2000), which is widely used in social science literature. Moreover, Decoster et al.'s method was originally designed to match income and budget survey data, which bears a similar data pattern to the farm survey datasets used in this study.

In this paper, the implicit option from Decoster et al. (2007) is employed. This involves directly linking the nutrient management survey data with the national farm survey microdata, without being dependent on strong theoretical assumptions of the model. The Mahalanobis distance equation is used to concatenate or link the two datasets. Decoster et al. (2007) conducted a comparison of parametric and non-parametric estimations, demonstrating that both approaches yielded good results in terms of estimations closely aligning with actual budget values. According to Decoster et al. (2007) the Mahalanobis distance is stated as:

$$d\left(t_i, t_j\right) = \sqrt{(t_i - t_j)' \cdot \Sigma^{-1} \cdot (t_i - t_j)} \qquad (3)$$

t_i is capturing of overlapping factors of observation i in the aimed/targeted data and t_j is variable of the source dataset. Σ in turn is a covariance matrix of coinciding variables of the donor or source data.

The Mahalanobis distances were calculated using overlapping variables such as total land farmed (hectare), total land rented (hectare), and total tillage area (hectare) to perform the statistical matching between the target and source datasets. Additional overlapping variables included farm systems (e.g., cattle, dairy, sheep, or tillage), main soil type on the farm, gender of the farmers, age of the farmers, whether they work full-time or part-time on the farm, and farm income bands (consisting of 8 bands in total).

To assess the quality of the match and whether the matched variables followed a similar pattern, the Kolmogorov–Smirnov test was used (Kolmogorov, 1933; Smirnov, 1933). This test compares the distributions of two matched variables. Table 6.4 presents the output of the Kolmogorov–Smirnov test, where the deciles of livestock unit values from the nutrient management planning and national farm survey were examined. The livestock unit was selected as the sample for the test. The D-statistic represents the largest distributional distance function between the two survey values, and the P-value indicates the probability value. The results of the test showed that the majority of deciles had the largest cumulative probability distance around 0.5, while deciles 7-9 exhibited relatively high cumulative distances among the matches. Furthermore, all D-statistic values were statistically significant with probability values below 0.05.

Table 6.4. Livestock unit (decile) Kolmogorov–Smirnov test of nutrient management planning survey and national farm survey datasets after the statistical matching

Livestock Unit	**D-statistic**	**P-value**
Decile 1	0.64	0.00
Decile 2	0.52	0.00
Decile 3	0.48	0.00
Decile 4	0.35	0.00

Decile 5	0.52	0.00
Decile 6	0.52	0.00
Decile 6	0.59	0.00
Decile 7	0.97	0.00
Decile 8	1.00	0.00
Decile 9	1.00	0.00
Decile 10	0.82	0.00

6.3.7. Cost-Benefit Estimation

The return from liming is defined as the benefit less cost of liming. The cost side is calculated as the amount of lime needed per hectare or acre for a given pH level. According to the North Carolina Department of Agriculture and Consumer Services[12], a farm's required lime amount is estimated as:

$$Lime\left(\frac{tonne}{acre}\right) = Ac \cdot \left[\frac{target\ pH - current\ pH}{6.5 - current\ pH}\right] - RC, \tag{4}$$

Where the Ac or Ac value is a measurement of exchangeable acidity and RC is stated as a residual credit or the leftover lime amount from previous application. The 6.5 amount refers to the optimal pH level for grass growth. The estimated quantity of lime per farm is then multiplied by the average cost of liming in Ireland (€25 per tonne), which includes the cost of lime and spreading it.

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[12] NCDA&CS: https://www.ncagr.gov/agronomi/

The second component of the economic return from lime application is the direct benefit derived from achieving the optimal pH level. According to Zimdahl (2015), different pH levels result in varying percentages of nutrient absorption or efficiency in the soil. Table 6.5 displays the quantities of macronutrients absorbed by the soil at specific pH levels. It is evident that a neutral pH level of 7.0 allows for the highest absorption of nitrogen, phosphorus, and potassium by farmland soils, resulting in 0% wasted fertilizer when applied.

Table 6.5. Efficiency rate of macronutrients at given pH level

Soil Acidity	Nitrogen	Phosphorus	Potassium	Wasted Fertilizer
Extremely Acid — 4.5 pH	30%	23%	33%	71.34%
Very Strong Acid — 5.0 pH	53%	34%	52%	53.67%
Strongly Acid — 5.5 pH	77%	48%	77%	32.69%
Medium Acid — 6.0 pH	89%	52%	100%	19.67%
Neutral — 7.0 pH	100%	100%	100%	0.00%

After calculating the inefficiency rate (wasted fertiliser) of macronutrients for each farm based on its soil pH level, we will use this information to estimate the monetary value of wasted macronutrients, considering the farm's current macronutrient purchases. In this study, the monetary value of wasted purchased macronutrients is considered as the amount saved (benefited) if farmlands were to reach the optimal pH level. This provides a direct benefit from the saved fertilizers.

6.4. Results

In this section, the results are presented in two main parts. The first part focuses on the spatial distribution of farmers' intentions regarding lime application, based on the TPB constructs. It begins by examining whether the conditional independence assumption holds in the context of statistical matching. Furthermore, this part explores the impact of explanatory factors, such as farm gross output, costs, and environmental elements, on farmers' intentions to apply lime.

In the second part, the analysis delves into the cost and economic benefit of applying lime. The results of this part are presented in terms of monetary values and identify hot-spot and cold-spot areas. By incorporating these two parts of the results, this paper offers unique insights into the behavioural aspects of lime application and sheds light on the economic considerations of liming practices.

6.4.1. The Validity of Conditional Independence Assumption (CIA)

Before conducting the statistical matching, this paper introduces the Conditional Independence Assumption (CIA) as the basis for the matching process. The CIA assumes that when statistically matching one dataset (NMP data) with overlapping variables (X and Y) to another dataset (NFS data) with overlapping and non-overlapping variables (X and Z), there should be a valid association between Y and Z only through the X variables, meaning that Y and Z are directly independent of each other.

In the paper's analysis, the overlapping variables (X) include total land farmed, total land rented, total tillage area, farm systems (e.g., cattle, dairy, sheep, or tillage), farm's main soil type, farmer's gender, age, full-time or part-time work on the farm, and farm income bands (8 bands in total). The Y variables represent intention, attitude, perceived behavioural controls, subjective norms, and perceived resources. The Z variables are net benefits of lime and spatial variables. The paper argues that the overlapping variables (X) play a significant role in explaining the Y and Z variables since they define the farm's characteristics and resources, which in turn heavily influence the Y and Z factors.

Table 6.6 displays the correlation between the overlapping and non-overlapping variables with intention. The binary logistic regression results reveal varying explanatory coefficients for farm intention. The relatively high R-squares in the table indicate that the independent/overlapping variables used in the statistical match explain a reasonable portion of the dependent/non-overlapping variables, supporting the validity of the conditional assumption with a moderate degree of explanatory weight.

The table shows that attitude's coefficient (-0.37) indicates a negative relationship with a statistically significant impact (***) in regard to farmers intention to lime their farmland. It suggests that as attitude decreases, the likelihood of following lime application advice increases by a factor of 0.69. The subjective norm coefficient of 0.69 states that a positive relationship exists between subjective norms and intention. As subjective norms increase, the likelihood of adopting lime advice nearly doubles (1.99). The perceived behavioural control's coefficient of 0.38 is showing a positive impact. As perceived behavioral control increases, the intention to follow lime advice rises by a factor of 1.46. In the case of perceived resources; the coefficient stands at 1.54, indicating a strong positive impact. A higher perception of resources increases the intention to adopt lime application advice by a factor of 4.66.

In terms of farmer characteristics and their coefficients the cattle, dairy, and tillage systems all show positive relationships with significant impacts on farmers' intention to stabilze farm pH level. Farm size and farm family income coefficients show that both have very small, almost negligible coefficients indicating minimal influence on intention. However, in respect to age groups, younger farmers (age <35) show a strong negative impact, while older groups exhibit negative but lesser impacts on intention. Finding also show that higher education levels display significant positive impacts on intention. The male gender also positively influences intention.

Agricultural advisor (at 90% level) and low pH (at 99% level) have small but statistically significant impacts on intention. Soil group of 1 and 2 have varied impacts on intention. The number of observations, chi-square values, and the pseudo R-squared value signify the model's overall fit and explanatory power. The model explains about 73% of the variance in farmers' intention to adopt lime application.

Table 6.6. Binary logistic regression of overlapping variables and non-overlapping variables with farmers intention to apply lime.

TPB	Coeff.	Std.err	95% Conf. Interval		Exponent of Coeff.
Attitude	-0.373^{***}	0.03	-0.43	-0.32	0.69
Subjective Norm	0.684^{***}	0.02	0.65	0.72	1.98
Perceived Behavioural Control	0.382^{***}	0.01	0.36	0.40	1.46
Perceived Resources	1.528^{***}	0.02	1.49	1.57	4.61
Farm and farmer characteristics					
Cattle system	0.212^{***}	0.06	0.10	0.33	1.24
Dairy system	0.505^{***}	0.06	0.38	0.63	1.66

Tillage system	0.691^{***}	0.12	0.46	0.92	2.00
Farm Size (hectare)	0.068^{***}	0.00	0.06	0.07	1.07
Farm Family Income	0.000^{***}	0.00	0.00	0.00	1.00
Age <35	-5.300^{***}	0.21	-5.70	-4.90	0.00
Age 35-44	-2.889^{***}	0.22	-3.32	-2.45	0.06
Age 45-50	-5.460^{***}	0.19	-5.84	-5.08	0.00
Age 51-64	-3.339^{***}	0.18	-3.69	-2.99	0.04
Formal education					
College/University/Post-grad degree	5.956^{***}	0.23	5.50	6.41	386.02
Professional qualification at diploma level	7.004^{***}	0.19	6.63	7.37	1100.53
Leaving cert	5.126^{***}	0.18	4.78	5.48	168.30
Gender (Male)	1.711^{***}	0.14	1.43	1.99	5.53
Agricultural advisor	0.188^{**}	0.06	0.07	0.31	1.21
Low pH	-0.275^{***}	0.05	-0.37	-0.18	0.76
Net Benefit	0.001^{***}	0.00	0.00	0.00	1.00
Soil Category					
Soil Group 1 (Classes 1 and 2)	-0.434^{***}	0.09	-0.61	-0.26	0.65
Soil Group 2 (Classes 3 and 4)	0.617^{***}	0.10	0.43	0.80	1.85

Number of observations	86310
LR chi2(21)	52123.51
Prob > chi2	0.00

Pseudo R2	0.73

Notes: Significance levels *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Intention=1 is farmers responding “Strongly agree” and “Agree” with intend to apply lime.

Intention=0 is farmers responding “Strongly Disagree” and “Disagree” with intend to apply lime.

Low pH = 1 is pH level for a farm is lower than 6.5. Low pH also refers to a need to apply lime.

[a] Reference group for farm system is sheep system.

[b] Reference group for age is group 65+.

[c] Reference group for formal education is primary level.

[d] Reference group for soil category is group 3 (classes 5 and 6).

Supporting table 6.6 findings, the results of table 6.7 show the marginal effects derived from a binary logistic regression model examining the Theory of Planned Behavior (TPB) variables, and various farm and farmer characteristics affecting farmers' intentions regarding lime application. In the case of attitude, a decrease in attitude by 1 unit results in a decrease in the likelihood of adopting lime advice by 0.012 units, while an increase in subjective norms by 1 unit leads to a 0.022 unit increase in the likelihood of adopting lime advice. In regard to perceived behavioural control, a 1 unit increase in perceived behavioral control raises the likelihood of following lime advice by 0.012 units. Similary, an increase in perceived resources by 1 unit elevates the likelihood of adopting lime advice by 0.049 units.

The table 6.7 also suggests that cattle, dairy, and tillage systems show positive marginal effects, influencing the likelihood of adopting lime advice positively, while farm size and family income have very small marginal effects, indicating minimal influence on the likelihood of adopting lime advice. In respect to age groups; younger age groups show strong negative marginal effects on the likelihood of adopting lime advice, while older groups exhibit negative but lesser effects. Higher farmers’ education levels display significant positive marginal effects on the likelihood of adopting lime advice. Agricultural advisor and low pH level have small but statistically significant marginal effects on the likelihood of adopting lime practices. Soil groups 1 and 2 have varied marginal effects on the likelihood of adopting lime nutrient management advice.

Table 6.7. Marginal effects of binary logistic regression for the prediction of farmer intention to apply lime.

TPB	Marginal effects	Std.err	95% Conf. Interval	
Attitude	-0.012***	0.001	-0.014	-0.010
Subjective Norm	0.022***	0.001	0.021	0.023
Perceived Behavioural Control	0.012***	0.000	0.011	0.013
Perceived Resources	0.049***	0.000	0.048	0.050
Farm and farmer characteristics				
Cattle system	0.007***	0.002	0.004	0.011
Dairy system	0.018***	0.002	0.014	0.022
Tillage system	0.022***	0.004	0.015	0.030
Farm Size (hectare)	0.002***	0.000	0.002	0.002
Farm Family Income	0.000***	0.000	0.000	0.000
Age <35	-0.205***	0.012	-0.228	-0.181
Age 35-44	-0.073***	0.007	-0.087	-0.060
Age 45-50	-0.218***	0.011	-0.240	-0.197
Age 51-64	-0.091***	0.006	-0.103	-0.079
Formal education				

College/University/Post-grad degree	0.312^{***}	0.011	0.292	0.333
Professional qualification at diploma level	0.334^{***}	0.010	0.315	0.353
Leaving cert	0.292^{***}	0.010	0.272	0.312
Gender (Male)	Not estimable			
Agricultural advisor	0.004^{*}	0.002	0.000	0.008
Low pH	-0.007^{***}	0.002	-0.010	-0.004
Net Benefit	0.000^{***}	0.000	0.000	0.000
Soil Category				
Soil Group 1 (Classes 1 and 2)	-0.013^{***}	0.003	-0.019	-0.007
Soil Group 2 (Classes 3 and 4)	0.022^{***}	0.003	0.015	0.028

Notes: Significance levels *** p < 0.01, ** p < 0.05, * p < 0.1.

“Not estimable” refers to when the effect wasn't estimated or didn't yield meaningful results in the model.

Table 6.8 shows correlation coefficients of low pH level with four behavioural variables and net farm benefit. Table values indicate the strength and direction of the relationship between each variable with low pH level. The attitude variable shows a positive correlation of 0.037, suggesting a weak positive relationship with low pH or the need to apply lime. Similarly, subjective norm exhibits a positive correlation of 0.013, albeit also relatively weak. Conversely, both perceived behavioral control and perceived resources display negative correlations of -0.015 and -0.017, respectively, indicating weak negative relationships with the need to lime farmlands. Notably, net benefit stands out with the highest correlation coefficient of 0.078, implying a relatively stronger positive relationship compared to the other variables in this set.

Table 6.8. Correlation coefficients of low pH level with behavioural variables and net benefit.

	Corr. Coefficient	P-value
Attitude	0.037	0.00
Subjective Norm	0.013	0.00
Perceived Behavioural Control	-0.015	0.04
Perceived Resources	-0.017	0.00
Net Benefit	0.078	0.00

Notes: Low pH = 1 is a pH level of a farm if it is lower than 6.5. Low pH also refers to a need to apply lime.

Table 6.9 shows correlation coefficients of low pH level with with low, medium, and high benefit groups. Table values indicate the strength and direction of the relationship between each variable with low pH level. It can be seen that low and medium benefit farms have a negative correlation with low soil pH levels. On contrast and as expected, the high benefit cohort is positively associated with low pH levels.

Table 6.9. Correlation coefficients of low pH level with low, medium, and high benefit groups.

	Corr. Coefficient	P-value
Low Benefit	-0.026	0.00
Medium Benefit	-0.048	0.00
High Benefit	0.081	0.00

Notes: Low pH = 1 is a pH level of a farm if it is lower than 6.5. Low pH also refers to a need to apply lime. Low benefit refers to the lowest tercile of benefit from applying and balancing pH level, while medium and high benefit groups refer to average and top benefit groups.

Table 6.10 shows correlation coefficients of farmers' intention with low, medium, and high benefit groups. Table values indicate the magnitude of coefficients and their statistical significance as p-values. The table shows that low and medium benefit group farms have positive correlations with farmers' intention to apply lime and increase their soil pH level. Surprisingly, the high benefit category is negatively correlated with farmers intention, which means farmers who benefit the most don't have a positive intention to carry out lime management of their farms.

Table 6.10. Correlation coefficients of farmers' intention with low, medium, and high benefit groups.

	Corr. Coefficient	P-value
Low Benefit	0.007	0.01
Medium Benefit	0.020	0.00
High Benefit	-0.030	0.00

6.4.2. Spatial Distribution of Cost and Benefit of Liming

Farmers may be more motivated to follow lime recommendations if they have a clear understanding of the economic benefits, they will gain from stabilising their soil pH level. To address this, the paper presents the spatial distribution of the net benefit of liming (shown in figure 6.2), which represents the economic return after adjusting the pH level of farmland soil. The net benefit in figure 6.2 is calculated by subtracting the cost of applying lime from the overall benefit.

The results reveal that the North and South regions of the country have higher net benefits per hectare after stabilizing their farmland's pH level. On the other hand, the midlands and East regions have relatively lower net benefits after lime application. Farms in the West of Ireland show a medium level of benefit if they were to apply lime and achieve stable soil pH levels.

Farms in regions with high net benefit values have the potential to earn more by stabilizing their soil pH levels compared to farms in regions with lower net benefit values. The reason for this lies in the fact that farms with relatively lower (acidic) soil pH levels stand to benefit the most from adopting lime recommendations. Conversely, farms with more stable pH levels will experience smaller or no significant net economic benefit, as their pH levels are already close to the stable level, leaving little room for improvement.

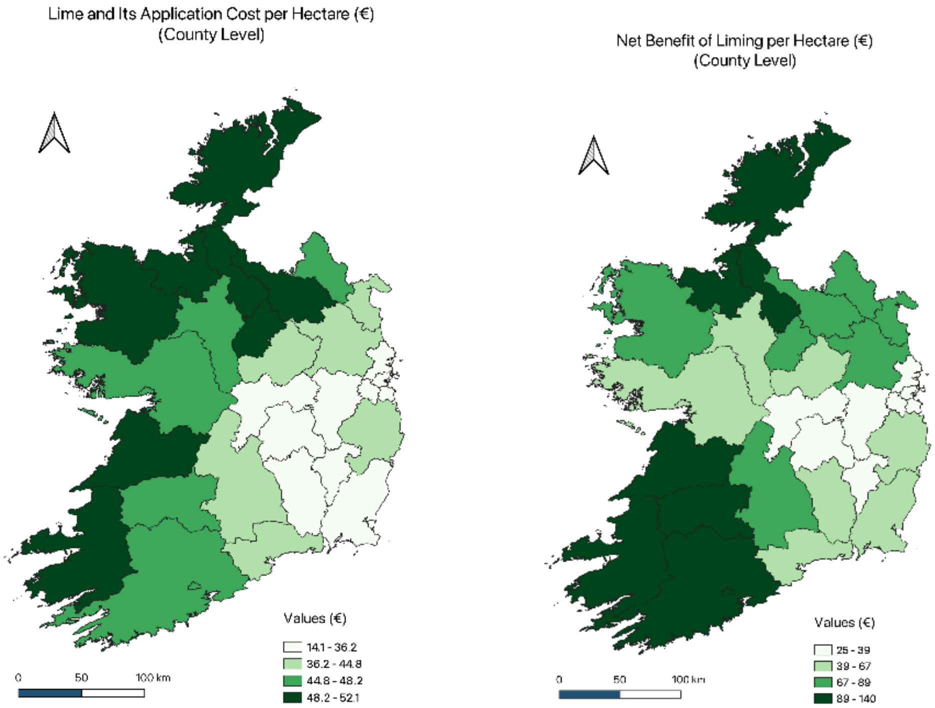


Figure 6.2. Cost (€) (to Stabilise pH Level) and Benefit (€) of Liming per hectare.

To gain insights into which regions of the country will benefit the most and least from lime application as a result of farmers intention to carry out lime management measures, a hotspot analysis of famers intention to apply lime can be estimated. Unlike simply plotting a map of farmers intention values, the hotspot analysis identifies statistically significant hot spots and cold spots, providing values in terms of standard deviations. Figure 6.3 illustrates the hotspot analysis of farmers' intentions to perform lime management practices.

Hot spots are observed in the North, North-West, and South regions. These hot spots indicate that farmers in these regions have the highest intention in adopting lime application recommendations and achieving stable pH levels. It also suggests that these regions may have relatively lower pH levels, making lime application particularly beneficial. Conversely, cold spots are found in the East, South-East, and part of midlands, indicating areas where the intention may be comparatively lower. In summary, the hotspot analysis provides valuable information about the regions where farmers will experience the most significant economic benefits from lime application with increased farmers' intention to do so, highlighting potential areas for targeted lime nutrient management strategies.

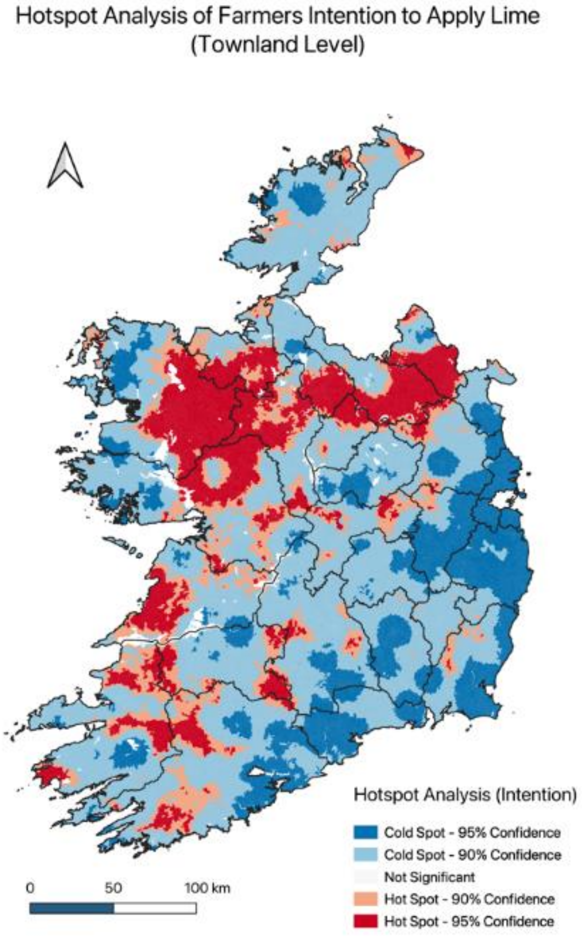


Figure 6.3. Hotspot analysis of farmers' intention to apply lime.

6.4.3. Localized Association of Behavioural Factors with Farmers Intention to Lime

Determining whether the regions that require lime the most align with the highest behavioural intention among farmers is crucial to understand their motivation for lime application and stabilizing soil pH levels. It is essential to differentiate between farmers who need to undertake liming due to low pH levels and farmers who actually want to lime their farmland. Understanding the spatial statistical association between farmers' behavioural intention and the need for lime application can provide valuable insights for farm advisors, agricultural researchers, and policymakers to tailor their decisions and actions based on localized farming conditions.

In summary, the geographically weighted regression analysis helps shed light on the connection between farmers' behavioural intention and the necessity for lime application, allowing for a better understanding of farmers' motivations and lime nutrient management practices in specific geographic regions. Figure 6.4 shows the geographically weighted regression coefficients of attitude and perceived behavioural controls after regressing them with farmers intention to apply lime. The part of the West, East and South have positive explanatory coefficients of attitude and perceived behavioural control. While partially the midlands, North and South-East in case of perceived behavioural control and the midlands and West-South in case of attitude have negative relationship with farmers intention to follow lime recommendations. The positive relationship of attitude in some regions suggest that farmers have positive evaluation of applying lime, while the negative coefficients represent the opposite. The regions with positive association with perceived behavioural control explain farmers perception relatively as an ease, in terms of farmers ability in follow liming practices. The areas with negative spatial relationship of perceived behavioural control indicate farmers perception toward liming as difficult.

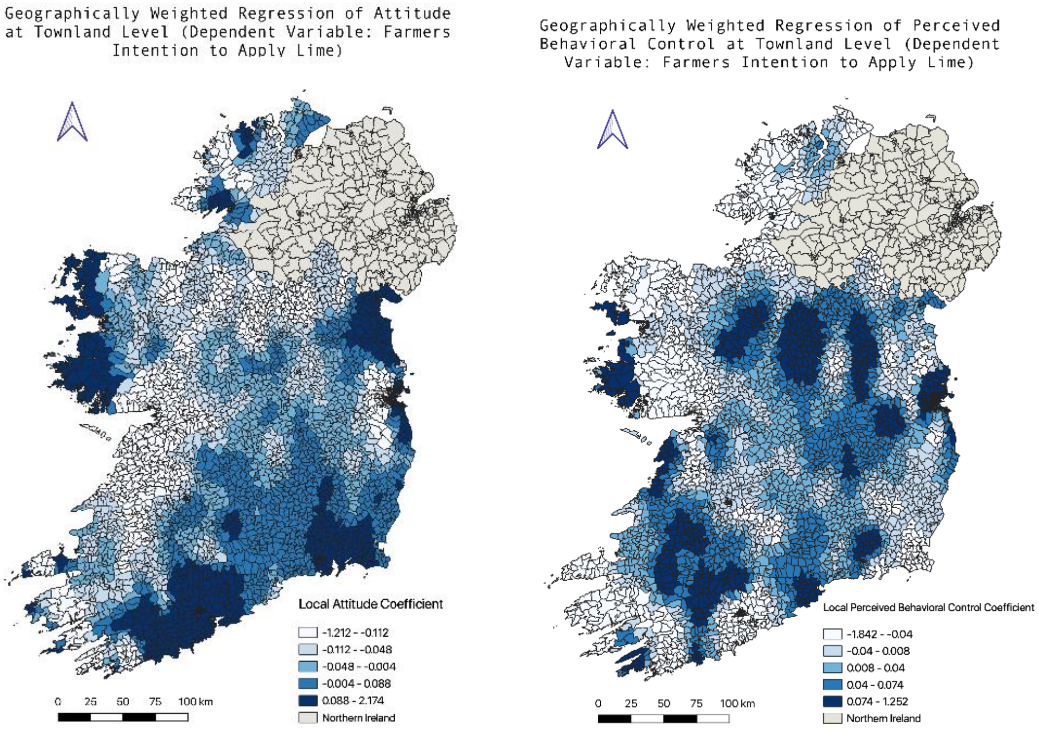
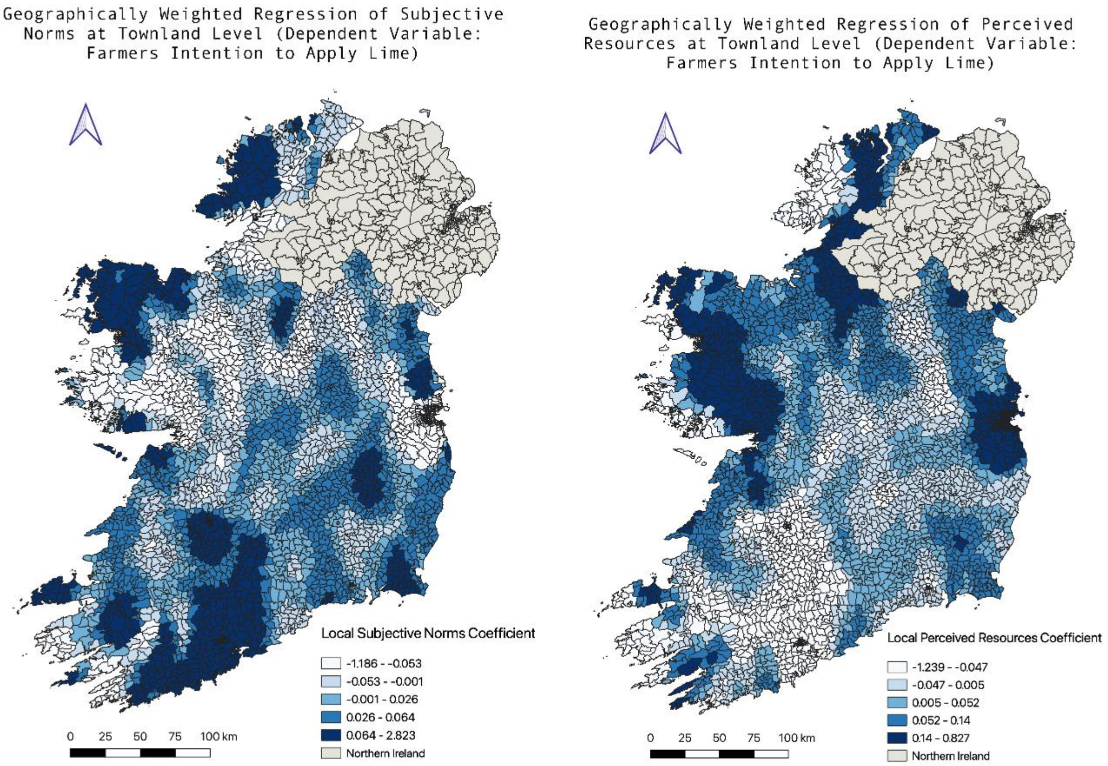


Figure 6.4. Regression coefficients of Attitude and Perceived Behavioural Control

Geographically weighted regression coefficients of subjective norms and perceived resources is shown in Figure 6.5. The North, North-West and main the South have positive subjective norms coefficients in respect to farmers intention to apply lime, while part of the midlands and West have negative subjective norms relationship. The positive association of perceived resources are seen partly in the North, West and East, while the South and part of the midlands show negative localised geographical relationship with farmers intention to carry out lime advised practices. Farmers positive subjective norms coefficients represent farmers belief that majority of people/farmers surrounding her/him approve the practice of liming, while the opposite (disapproval) is true in the regions with negative subjective norms coefficients. In case of perceived resources, positive relationship toward farmers intention to apply lime can result if farmers believe they have enough time, financial and labour resources to apply lime. If a region has negative perceived resources relation with farmers intention to lime, then farmers in this location have pessimistic perception of their resource capabilities to follow lime recommendations and lime their farmland.


Geographically Weighted Regression of Subjective Norms at Townland Level (Dependent Variable: Farmers Intention to Apply Lime)

Geographically Weighted Regression of Perceived Resources at Townland Level (Dependent Variable: Farmers Intention to Apply Lime)

Figure 6.5. Regression coefficients of Subjective Norms and Perceived Resources

6.5. Conclusion and Discussion

There are different economic and behavioural motivations, and different biological implications of these motivations in the different parts of the country. There is a bit of endogeneity where the commercial farmers in some areas with the better land and they are more reliant on farming and farm income. And because they are getting higher commercial returns, they are more focused on their farms, management and improvement of their farms, so they have better behavioural attitudes. The better behavioural attitudes in turn lead to improved farmers intention and higher probability that they actually follow liming advice.

While economic return from application of lime to stabilise the soil pH level is widely known and researched, only part of farmers actually follows lime application recommendations (Daxini et al., 2018). The study of this paper addresses behavioural and economic aspects of lime application. Initially the paper shows the spatial distribution of attitudes, subjective norms, perceived resources, perceived behavioural controls and behavioural intention toward lime application practices. Then it quantifies the impact of different factors influencing farmers intention to lime their farmland to stabilise the soil pH level. Finally, the economic elements, such as cost of liming and net benefit of lime application is analysed.

The first variable of the theory of planned behaviour is the attitude. The findings of this research point that farmers attitude changes spatially and that farmers may have a positive or negative attitude due to past experiences or obtained knowledge regarding the liming practices. Although there is a scarcity of attitude literature in the liming field to compare the papers results with, the importance of attitude is discussed widely. For instance, the attitude variable is found to influence positively the household waste recycling intention (Nigbur et al., 2010). While Quintal et al. (2015) show that wine value and winescape have a major positive impact over wine tourist attitude, which then effects behavioral intention to the winery.

The perceived behavioural control is the second variable of the theory of planned behaviour. The results of the paper suggest that perceived behavioural controls have geographically heterogeneous effect over farmers intention to apply lime. This behaviour could be the outcome of farmers perception of their ability to understand and carry out lime application recommendations. There is not enough literature of perceived behavioural controls explaining lime application to do comparison with this study, however many researches have supported role of this variable of the theory of planned behaviour. Castanier et al. (2013) found moderate influence of perceived behavioural controls upon road traffic violations. Phipps et al. (2015) state that perceived behavioural controls impact intentions of anaesthetists to commit violation.

The subjective norms are the third variable of the theory of planned behaviour that deals with codes of behaviour that represent a cluster of people. The paper shows that this variable has influential effect over farmers intention for liming that varies across the country. Varying spatial distribution of subjective norms can result because of farmers having different customary or group norms changing from one place to another. The literature of subjective norms, such as Al-Swidi et al. (2014) show that subjective norms significantly impact attitude toward buying organic food. While Karimy et al. (2015) suggest that the correlation analysis found subjective norms to be positively affecting intention to smoke.

The perceived resources variable is the part of extended theory of planned behaviour discussed and analysed by Zeweld et al. (2017). This variable tries to explain resources side, such as financial, labour and time of the theory of planned behaviour. Finds of this paper shows this variable, consistent with other variables of the theory planned behaviour to be spatially varying and having different geographical impacts across the regions. This locational heterogeneity of perceived resources alludes that farmers have different spatial finances and labour resources to be willing for up-take of lime application advice. Daxini et al. (2018) suggest that perceived resources are positively and significantly associated with farmer intention to adopt nutrient management planning practices.

From the results of geographically weighted regression the farm direct and overhead costs have different spatial pattern. This suggests that two cost types explain farmers intention to stabilise soil pH level differently. For instance, overhead costs of the North are negatively associated with farmer intention to liming, where direct costs have positive relationship with the same region. This finding has important implication to other researchers and policymakers deciding to take research and policy initiatives regarding costs of lime nutrient management planning. Liming costs is widely discussed in different contexts in the literature, such as Tumusiime et al. (2011) suggest advised level of nitrogen is lowered by 13% after taking into account cost of liming. While Liu et al. (2003) carries out a simulation to find required amount of lime, as calcium carbonate and to show cost liming associated with apply it. However, the field of literature most relevant to the study of this paper, in case of liming costs' relationship with farmers behavioural intention hasn't been explored yet.

Lime and application costs are the important element farmers factor in when deciding to follow liming recommendations. Estimated spatial distribution of needed liming cost to stabilise soil pH level (6.3-7.0) shows that some regions may need to spend more in order to neutralise their farmlands soil acidity, while other regions need small to no cost to balance their pH level as their lands already have adequate pH level. For farms with relatively small profit liming costs can be a significant burden to carry given their soil pH level is at the lower range (3.0-4.0), while for the high profit farms lime application costs may be negligible. Calculating cost of liming needed to balance soil pH level can help policy analysts and researchers as cost policy tool and cost research background to study further. The cost analysing of per hectare complements existing nutrient management plans and aids to make more accurate policy and research decisions.

The net benefit of liming in this paper is calculated as the total benefit of liming after subtracting the total costs of lime application. Estimating net benefit of liming incentivises farmers to carry out lime recommendation advice, as they will know beforehand how much they are going gain if they stabilise their soil pH level and improve macronutrients absorption. Farm advisors can also use the finding of this study to give farmers recommendations based on spatial location of farmers. Additionally, policymakers can make lime nutrient management policy decisions based on this ex-ante analysis of financial gain per hectare.

To conclude, the papers study can be used by other researchers as a benchmark before carrying out lime and nutrient management planning research. The finding can also be deployed as a policy guidance by policymakers taking nutrient management planning initiatives. Irish farmers and farm advisors can use this paper as a base knowledge to understand spatial liming practices, behavioural factors of lime application, cost and benefit of stabilising the soil pH level. Additionally, the findings of the paper serve as an extension to the literature of the theory of planned behaviour and lime nutrient management planning. Finally, the results of the paper answer the important questions of if there is a need to follow lime nutrient management practices is their positive farmers intention to uptake lime recommendations and how they are spatially distributed.

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7. CHAPTER SEVEN: The Importance of Spatial Disaggregation in Providing Agricultural Market Outlook Advice

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Abstract

Financial management in agriculture is crucial for farmers to navigate economic uncertainties such as fluctuating costs of fertilizers and fodder, or variations in sales per unit of output. However, many existing financial planning tools for farmers struggle with widespread adoption due to challenges like recording every purchase and sale transaction, and then processing this data for financial planning insights. This paper introduces an alternative tool designed to enhance existing farm financial planning or decision support systems. This new tool, which incorporates a spatial aspect, is particularly geared towards farmers who are less active in financial planning. It leverages a spatial microsimulation approach and is based on the SMILE model. The data used to develop and test this tool comes from Teagasc's National Farm Survey, spanning from 2001 to 2014. One key advantage of this tool is its ability to provide spatially detailed benchmarking information at the townland level. This is shown to be more effective for improving financial planning among less engaged farmers than general regional or national level data. Furthermore, this tool simplifies the process by eliminating the need to input each financial transaction, making it more appealing, especially to small-scale farmers, and encouraging greater involvement in economic planning.

Key words: Decision Support, Agriculture, Modelling, Output, Costs

7.1. Introduction

In the market-driven agriculture sector, both input and output prices significantly influence farm incomes, a trend that has become more pronounced with the increased volatility of prices since the mid-2000s. Understanding how price fluctuations affect incomes is crucial for both farm-level decision-making and policy formulation, especially considering the varied impact on different farmers.

The complexity of the agricultural market environment, characterized by higher volatility, complex investment scenarios, and viability challenges (O'Donoghue et al., 2016), has heightened the importance of farmers' involvement in financial management. Enhanced financial management is necessary across all profitability levels. However, farmers tend to adopt agricultural technologies and practices more readily than financial strategies (Hennessy and Heanue, 2012). This inclination highlights the need for more comprehensive planning to bolster resilience in a complex farming environment. Additionally, it was been found that decision support tools can enhance better engagement and mitigate conflict among stakeholders (Mukhtar and Bahormoz, 2022).

Despite the availability of tools like the eProfit Monitor (ePM) decision support system (Morrow et al., 2004) to aid in financial management and planning, their adoption has been limited. Although the use of the eProfit Monitor has grown significantly, with about 10,000 farmers employing it, this number still only represents a small percentage of the overall farmer population. As discussed by many scholars, big data decision support systems (Alaskar et al., 2021) and digital transformation (Alhassan and Soui, 2021) would also help agricultural participants to take advantage of these systems/tools.

The foundational element of the farm financial information system is its biophysical methodological framework. Weather is a primary time-variant agronomic factor influencing grass growth. To comprehend grass growth drivers, it's essential to gather weather and soil data at specific grid points, aligning with remote sensing-based grass growth measurements. Analyzing the effects of varying agronomic conditions and grass growth nationwide requires integrating this data with farm data, management decisions, and outcomes. This integration is then connected to market prices to model the market effects resulting from the interplay of these biophysical elements. For instance, Rao et al. (2016) analyse the milk market and its linkage to the household income within dairy hubs.

We utilize spatial microsimulation methods to create a base dataset, building upon methods developed in the creation of the Teagasc Simulation Model of the Irish Local Economy (SMILE). Later in the modeling process, we analyze the output and cost impact at both localized and farm levels for individual farms across the country by associating farm information with spatial dimensions. To achieve this, we utilize biological and economic data from farm systems, including animal demographics, feed supply and demand, imported feed, other costs, and animal outputs. This analysis involves integrating spatially referenced farm and biophysical data to generate farm-level output and cost results.

Market outlook analyses can be based on farm-level data or farming systems. Teagasc’s Annual Situation and Outlook (Teagasc, 2016) for the Irish agricultural sector provide detailed information on agricultural macroeconomics and microeconomics outlook for a given year and forecasts for the coming year. Farm systems-based market outlooks are also provided in this annual review, including systems such as dairy, cattle, sheep, tillage, pigs, and forestry.

Similarly, other countries' agricultural authorities and research institutes provide economic insights for the agricultural sector that are used by agricultural economists, farm advisors, and farmers to familiarize themselves with current conditions and form some expectations for the future. In the case of Teagasc's Annual Situation and Outlook for Irish agriculture, it is primarily based on Teagasc's own national farm survey data, while some other countries rely on central statistics office data or private survey companies. Additionally, market outlook information varies from country to country based on dominant farming systems (Teagasc, 2016).

In most cases, market situation output reviews and reports provided by agricultural government agencies or private agricultural institutes supply information at national, farm system, or spatial unit levels, such as county, state, or electoral district, and are not based on individual farms. Furthermore, the majority of existing agricultural market outlook advice reports are provided as averages, for example, national average, county average, or district average. However, for more accurate and specified information, individual farm-level analytical reports and advice should be given to farmers, farm advisors, and agricultural economists.

This paper focuses on the development of a Decision Support Tool to provide localized advice. The Decision Support Tool will include benchmark information, such as top, middle, and bottom in terms of farm market gross outlook, farm overhead costs, farm direct costs, and net farm profit. The Decision Support Tool provides benchmark information at the farm level, per unit of utilized agricultural area, and livestock unit. Additionally, this tool gives the most recent situation information of the agricultural sector by extracting data from the Central Statistics Office.

Generally, providers of agricultural advice and reports give information in the form of spatial aggregates (country, state, district) or averages of timeframes (year, quarter, month). By spatially aggregating and averaging a time period, a loss of precision of provided information for a farm can be seen, as averaged and aggregated information may not represent localized farm characteristics. Furthermore, averaged and aggregated information can be seen as a general guide for an averaged time period or spatially aggregated region, rather than a farm-specific decision support tool. Thus, the rationale for the development of a Decision Support Tool, which provides information for a specific farm with specific characteristics that is used as a benchmark tool.

This Decision Support Tool can be developed for any country, state, or region given the necessary base datasets and technical capability. This paper focuses on the Republic of Ireland as a case study. Ireland is mainly a grass-based livestock farming country, where it heavily relies on balanced rainfall, sunny weather, and soil characteristics. Given this, farms share agronomic and environmental characteristics within townlands, electoral districts, and even counties. For this reason, farms may want to see their comparison of output and costs with other farms in close proximity with similar farm characteristics, where the Decision Support Tool can serve as a needed tool. Moreover, farmers in Ireland have a low take-up rate with existing decision support tools, such as Teagasc's e-Profit Monitor, which requires recording and inputting all farm financial activities, where the Decision Support Tool, which only asks to enter bare minimum details, can aid and work alongside existing decision support tools.

Teagasc's Situation and Outlook (Teagasc, 2016), sometimes referred to as the Irish Situation and Outlook, gives information on the agricultural economic situation in Ireland for a given year and an outlook for the coming year. Provided situation and outlook prospects include all major Irish farming systems, such as dairy, cattle, sheep, and tillage. This annual review and outlook primarily utilize Teagasc's National Farm Survey and Central Statistics Office's data. The Annual Situation and Outlook give figures and statistics as a summary and in detailed form for specific variables, for instance, milk production, fertilizer purchases, and grass availability.

The structure of this paper is organized as follows. The theoretical framework and literature review are explored in Section 2. Section 3 explains the methodological choice of the paper and the data utilized. Section 4 provides the interpretation of results. The final section (Section 5) concludes the paper by discussing key points and contributions to the literature.

7.2. Theoretical Framework and Literature Review

The Predictive Decision Support Tool in this paper incorporates key elements of financial statements, specifically farm market gross output, farm overhead costs, farm direct costs, and net farm profit. The framework for this tool is outlined by O'Donoghue et al. (2016). These variables will serve as the basis for providing benchmark information at the farm level, per utilized agricultural area, and per livestock unit. Net farm profit, profit margin, or gross margin is defined as follows:

$$P_{net} = O_{market} - C_{direct} - C_{overhead}$$

O_{market} represents farm gross market output, which is total sales less purchase of livestock and crops. C_{direct} is total farm direct costs that are directly incurred by farm enterprises and can be allocated for each farm systems, while $C_{overhead}$ is total farm overhead/fixed costs which cannot be traced by a specific farm enterprise and recorded as costs incurred by a farm rather than a specific system.

The benchmark report information is categorized into top, middle, and bottom tiers, with each representing one-third of either farm output or costs. Alongside farm-level benchmark details, the Decision Support Tool furnishes information per utilized agricultural area. This encompasses market gross output, farm overhead and direct costs, and net farm profit, all divided by the farm's utilized agricultural area in hectares. Likewise, the benchmark per livestock unit is determined by dividing net farm profit, total farm gross output, and total direct and overhead costs by the farm's livestock unit. Although other farm related information could be also provided to further enhance the predictive tool, such as return on farm investments (Haydarov and Zhang, 2023), these details are very farm specific, and modelling them with a minimum input information from farmers is challenging.

Regarding agricultural economics information for farming enterprises, Teagasc's Irish Annual Situation and Outlook offers analyses and estimations on global economic trends, macro-events, and other factors like currency rates and oil prices that directly and indirectly influence the Irish agricultural sector. An ongoing macroeconomic event is Brexit (the United Kingdom leaving the European Union), significantly impacting Irish agriculture due to trade with the United Kingdom.

Macken-Walsh (2015) identifies challenges to the current use of advisor-managed interaction with existing decision support tools. Despite long-term benefits, farmers seem reluctant to engage in financial and business planning, perceiving it as too difficult or time-consuming, particularly in terms of the financial return on investment for lower-income farms. Research in the United States has indicated that farmers conducting detailed financial analyses are notably more profitable than those who do not make such calculations (Gloy and LaDue, 2003).

Even among highly educated new entrant Irish dairy farmers, McDonald et al. (2016) found that financial technologies such as annual financial accounting and cash flow budgeting are generally poorly understood. Dillon et al. (2008) report that 57% of Irish dairy farmers view financial management tools as time-consuming, suggesting that these tools are not part of many farmers' management repertoires, despite their necessity. Farm management tools can be also important when hedging disaster risks (Islam et al., 2021).

The challenge, therefore, is to develop decision support tools capable of providing benchmark information related to financial and technical aspects for users with varying degrees of engagement or skill. The additional challenge is to deliver this information in a way that does not involve transaction costs perceived as high by farmers.

For lower-income farmers to engage, the overhead of data collection and analysis needs to be less than that for existing decision support tools. Predictive approaches based on existing administrative and other real-time data sources can potentially provide personalized information with lower overhead, possibly enabling greater usage and engagement.

Using different assumptions regarding the efficiency of the top, middle, and bottom third of farms, our goal is to develop a predictive simulation of family farm income (output + subsidies – direct costs – overhead costs) for a farm with the characteristics observed in our framework. Although our data does not measure efficiency levels for the observed farm, we observe efficiency from other sources such as the Teagasc National Farm Survey.

To provide useful benchmark information for farms with these characteristics, we estimate what a top, middle, and bottom third efficient farm would look like. In other words, given the observed system, stocking rate, soil, altitude, and weather system, we predict the outcomes if a farm operated at different degrees of efficiency.

7.3. Methodology and Data

3.1. Methodology

Spatial microsimulation is a methodological approach involving analytical simulation or imputation at the micro level, which refers to entities such as households, enterprises and farms. This method is used to generate geographical distribution of specific variables or areas of interest. Understanding the geographic patterns of these relevant variables, which can have a significant impact on policy and economic performance, is the primary objective of spatial microsimulation modelling at farm level. In the case of Hynes et al., 2009, they used geographic microsimulation at farm level in order to assess the geographical effects of CAP on family farming incomes in rural Ireland. In the Netherlands, van Leeuwen and Dekkers (2013) and Ballas et al. 2013 analysed the geographical interaction between rural income, social policy, poverty and environmental change through spatial microsimulation analysis, while van Leeuwen and Dekkers (2013) examined the spatial distribution of off farm income.

O'Donoghue et al., in the years 2014 and 2017, developed and enhanced the SMILE model, which stands for the Simulation Model of the Irish Local Economy. This model primarily aims to assess the socio-economic impacts of various economic and policy shifts. The purpose of using the SMILE model in our analysis is to assess the impact of these changes in agricultural, rural, and environmental policy, which goes beyond the usual scope of economic and social policy change.

The sampling choices in the extended SMILE model, such as an environmental version (Haydarov et al., 2024) need to take a number of factors into account such as livestock (which is spatially heterogeneous), avoiding the income smoothing concerns of the sampling, and computational efficiency in terms of time and cost (O'Donoghue et al., 2017). The Quota Sampling (QS) method developed by Farrell et al. (2013) allows for the accommodation of these factors and is selected as the optimal methodological context for the extension of the SMILE model. QS is a probabilistic reweighting methodology that reweights survey data according to chosen constraint totals for individual pre-defined small areas.

Building on techniques employed in developing economic models at a catchment level, this research project establishes a foundational dataset. The project will enhance the current methodology by incorporating more recent data. Synthetic representative data is generated using data enhancement techniques to construct a spatial farm dataset synthetically. Due to the necessity for individual financial data, small area analysis cannot be utilized for this purpose (Ghosh et al., 1994). Therefore, a method like spatial microsimulation (Clarke, 1996) is needed to preserve both spatial and micro-level variability. Extensive literature, as outlined in O'Donoghue et al. (2014), covers various policy domains and employs methodologies detailed in Hermes and Poulsen (2012).

A methodology was developed in previous projects to develop a systems model linked to agronomic conditions for sheep and dairy systems. New data linking the Teagasc National Farm Survey to the Department of Agriculture Food and the Marine's AIMS administrative database will be used to improve the demographic information used in these models. We draw upon recent work in the Spatial Analysis Group in Teagasc in both, similarly other work has developed an understanding of the drivers of localised grass growth. This project will integrate this model within the predictive element. The dependent variable is based upon the grass growth data measured using remote sensing. Modelling is based on earlier work on a single site, such as by Hurtado-Uria et al. (2013), which analyses grass growth across on a varying spatial and temporal continuum. Widely utilized panel data analysis (Tanton and Vidyattama, 2010), with time series satellite data treated as cross sectional data at the pixel level, is the analytical bridge between remote sensing and agronomy approaches.

In practical terms, the process involves conducting quota sampling to determine the distribution of farm size, system, and soil type. However, this method does not consider localized agronomic factors like weather and altitude. To align this data with agronomic and grass growth data, statistical models will be developed using information from the Teagasc National Farm Survey. These models will analyze animal demographics, output, and cost variables based on farm and spatial features (geo-referenced cost and production functions). This approach integrates geo-referencing of the National Farm Survey with agronomic and environmental characteristics specific to each farm's location.

By employing the statistical models we have estimated, we can modify the dependent variables through microsimulation to consider specific agronomic factors at a local level. While previous studies have conducted post-calibration using alignment or calibration methods (Li and O'Donoghue, 2014), adjusting based on agronomic considerations has not been explored due to the lack of appropriately geo-referenced micro data. The methodology presented here will expand existing research, allowing these models to be applied for more detailed spatial analyses, such as examining the relationship between agriculture and water quality.

To establish a localized farm financial information system, we will create a diverse farm systems model for dairy, cattle, and sheep. This model will consider the agronomic, grass growth, system, and animal demographic characteristics of the farm. Specific components of the model will include modules for animal-specific nutrition requirements, feed demand, other inputs, farm output, market prices, and profit calculations. These modules will connect input and output volumes to prices using methodologies from Shalloo et al. (2004) and Crosson et al. (2006), adapted for diverse data sets. Price forecasts from Teagasc Agricultural Outlook modeling will be used for annual income and profit assessments. Subsidies will be treated as external factors due to the decoupling of CAP payments.

Our approach accommodates varying levels of farmer involvement, enabling them to access benchmark information categorized as top, middle, and bottom for a farm that aligns with their specific agronomic characteristics, size, stocking rate, and farming system. This means that farmers can compare their own performance against benchmarks set by farms similar to theirs in terms of key factors such as agricultural practices, farm size, livestock density, and operational methods. By providing this tailored benchmarking data, farmers can gain valuable insights into how their farm performance compares to peers with similar attributes, allowing for more informed decision-making and potential improvements in their farming practices. Working with other parts of the project, we will attempt to

- What is the most useful information required for farmers
- Understand what are the best ways of presenting information to farms
- Adapt the hypothesised framework described above to present the most appropriate data in the most appropriate ways to farmers

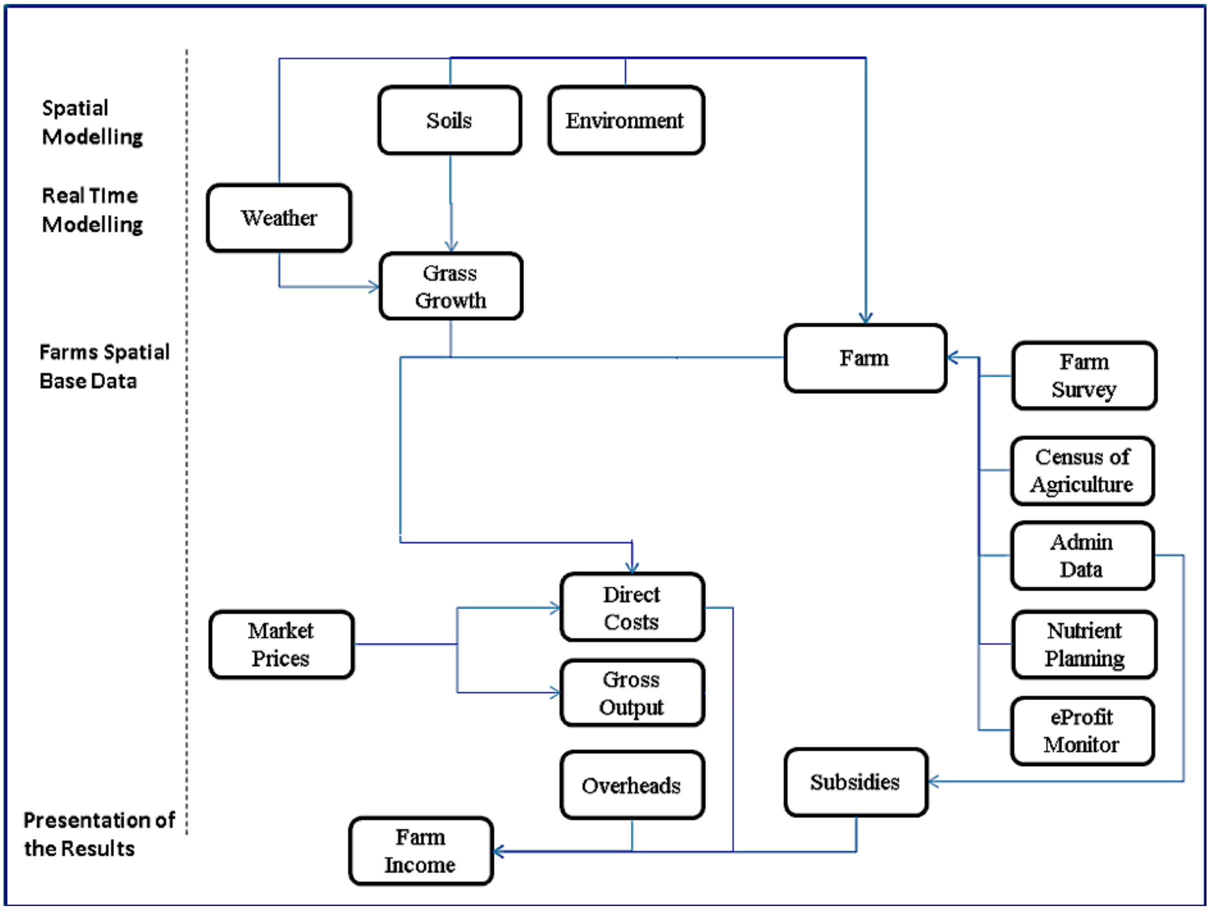


Figure 7.1. Structure of the FARMFIS Decision Support Tool. Source: Based on O'Donoghue et al. (2017)

The methodology employed in income generation here involves the use of a binary choice model, where binary events are expressed through a logit model. The objective is to simulate counterfactual values and then compare them with the sampled values, a commonly employed practice in the literature. For example, King et al. (2000) provide an interpretation of simulated counterfactual predicted values and expected values in a linear regression context. The logit model, as per O'Donoghue et al. (2017), is presented below as:

$$y_i^* = logit(p_i) = ln\frac{P_i}{(1-P_i)} = B_o + \sum_k \beta X_i^k + \varepsilon_i \qquad (1)$$

Where y=1 in the case of $y_i^* > 0$

The following equation is used in order to create a stochastic term of ε_i:

$$\varepsilon_i = ln\left(\frac{u_i}{1-u_i}\right) \qquad (2)$$

y=1 in the case of $u_i < logit^{-1}\left(B_o + \sum_k \beta X_i^k\right) = p_i$

A value of u_i can be presented as:

$$u_i = (Y = 1) * (r * p_i) + (Y = 0) * (p_i + \left(r * (1 - p_i)\right)) \qquad (3)$$

Where r is defined as a random uniform number.

The logit binary choice model requires parameters of β and a measure of the error term ε. In the model developed in this paper, panel data models are utilised, so the production and cost functions take the following forms, respectively:

$$\frac{V_{i,t}}{lu_{it}} = f_i\left(p_{M,t}^i, W_{CV,t}, A_{it}, K_{it}, L_{it}, X_{it}, ha_{it}, lu_{it}, u_i, v_{it}/\alpha, \beta, \upsilon, \delta, \mu\right) \qquad (4)$$

$$\frac{X_{CV}^{i}}{ha_i} = g_i^l\left(W_{CV,t}, A_{it}, K_{it}, L_{it}, X_{jt,j\neq i}, V_{it}, ha_{it}, lu_{it}, u_i, v_{it} / \alpha, \beta, \upsilon, \delta, \mu\right) \qquad (5)$$

where u_i is permanent and v_{it} is transitory effects.

The technical efficiency element (A_{it}) of the model is affected by agronomic conditions and weather (E_{it}), the soil type (Q_{it}), access to technical knowledge (H_{it}) and involvement in activities, e.g. environmental or forestry schemes and off-farm employment (O_{it}). If A^*_{it} represents efficiency and managerial skill, then:

$$A_{it} = A_{it}^{*} \times E_{it} \times H_{it} \times O_{it} \times Q_{it} \qquad (6)$$

$$A_{i0}, K_{i0}, L_{i0}, X_{i0}, ha_{i0}, lu_{i0}, u_i$$

The model draws a random number in order to account for the random noise v_{it}. Then it simulates each of the dependent variables in turn. For tractability and simplicity, the estimation and simulation of all of the equations are carried out independently (O’Donoghue et al., 2017).

Simulating the impact of price change is important, as it can take into account the heterogenous nature of price variation. Yet it remains uncertain what kind of calculation could accurately demonstrate this assumption, which is a typical aspect of any estimation. In our research and similar studies, the primary focus is on the variance from the baseline when compared to a specific counterfactual simulation, rather than the discrepancy between real data and forecasted data on an annual or monthly basis. To illustrate, our simulation method includes a measurement error ‘m’ when estimating a specific value ‘y’. The fundamental process of generating our data incorporates the traits of the model ‘$f(x) + e$’, in addition to this measurement error (equation 7).

$$y = f(x) + e + m \tag{7}$$

As it is not challenging to factor in the measurement error, caused by many factors such as attrition, presence of zero characteristics in this context, etc., the paper models the level with the error term 'y'.

$$y' = f(x) + e \tag{8}$$

After considering a change in x, x* in the simulation, we will utilize it with a measurement error in the level simulated:

$$y^{*\prime} = f(x^*) + e \tag{9}$$

Presuming that the measurement error is unrelated to the simulation, the contrast between the baseline simulated value and the alternative simulated value mirrors the actual difference, our emphasis is on the disparity between a baseline and an alternative simulation could be expressed with this formula:

$$y^{*\prime} - y' = f(x^*) + e - (f(x) + e) = f(x^*) + e + m - (f(x) + e + m) = y^* - y \tag{10}$$

7.3.2. Data

7.3.2.1. Teagasc National Farm Survey

The primary data source for the model is the Teagasc National Farm Survey (NFS), which collected data from 2001 to 2014. This survey is georeferenced and linked to environmental variables obtained from administrative datasets, such as census data. Approximately 1000 farms are chosen annually based on Central Statistics Office quotas and are assigned weights to ensure they represent the Irish farm population adequately (Teagasc, 2017). Participation in the survey is voluntary, and it excludes pig and poultry systems. As part of the EU's Farm Accountancy Data Network (FADN), the survey serves the purposes of policy analysis, research, and measuring financial and performance metrics.

The survey gathers key variables, including costs, subsidies, purchases, assets, liabilities, yields, inventories, and sales. Farms are categorized into systems such as dairy, cattle rearing, other cattle, sheep, and tillage. Poultry and pig systems are not represented in the Teagasc NFS due to the limited number of farms in these categories. However, the analysis in this paper encounters certain limitations when using NFS data. For instance, the standard output of farms in the survey is skewed towards larger farms, and those without livestock are underrepresented. For farms without animals, our approach involves excluding them from the census quotas and assigning them leasing income, enabling their inclusion in the target variable of gross output (Teagasc, 2017).

Table 7.1. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Year	16907	2007.57	4.25	2001	2015

Farm Gross Output (€)	16907	90305.44	95538.47	-1500	1162628
Farm Total Overhead Costs (€)	16907	28783.37	33337.51	0	605969.3
Farm Total Direct Costs (€)	16907	32128.61	41112.26	0	1113970
Total Livestock Units	16907	71	60.87	0	703.18
Utilized Agricultural Area (ha)	16907	54.33	45.95	0	1116.58

Source: Produced by Authors.

Table 7.1 provides a summary of the variables extracted from the National Farm Survey (NFS) utilized in the SMILE model and applied in the development of the Decision Support Tool. This table encompasses details such as the year, utilised agricultural area, farm overhead and direct costs, livestock units, and gross market output. Poultry and pig systems are not included in the Teagasc NFS due to the limited number of farms involved.

The Decision Support Tool will have benchmark farm information reagarding their respective counties, electoral districts, and townlands. In the Irish republic, there are 32 counties, 3,409 electoral districts, and approximately 60,000 townlands, with townlands being the smallest spatial unit. For farmers, receiving comparative benchmarks for their townlands, electoral districts, and counties proves beneficial. It enables them to assess their current cost and output situation and take necessary actions to adjust their output and/or costs as required.

7.3.2.2. Situation and Outlook

Examining previous annual review and outlook reports, such as the 2015 Situation and Outlook (Teagasc, 2016), allows one to observe the current economic estimates for the agricultural sector in 2014 and the projections for 2015. The report indicates that lower input expenditures characterized all grassland enterprises in 2014, driven by reduced use of feed and fertilizer, as well as decreased prices for these inputs along with fuel. The report highlights a favorable summer leading to above-normal cereal yields for major crops in 2014. However, a substantial global harvest resulted in a significant decline in cereal prices. Despite a slight reduction in cereal direct costs, this decrease proved insufficient to counterbalance the changes in output value. As a result, cereal margins decreased for nearly all crops in 2014.

Figure 7.2, extracted from the 2015 Situation and Outlook, illustrates dairy and beef feed use from 2009 to 2015 in kilograms of feed per livestock head. The data for 2014 is an estimation, while the 2015 data represents a forecast for the upcoming year. The visual representation indicates that the anticipated outlook for beef and dairy fodder use in 2015 is expected to remain at a level similar to the estimations for 2014.

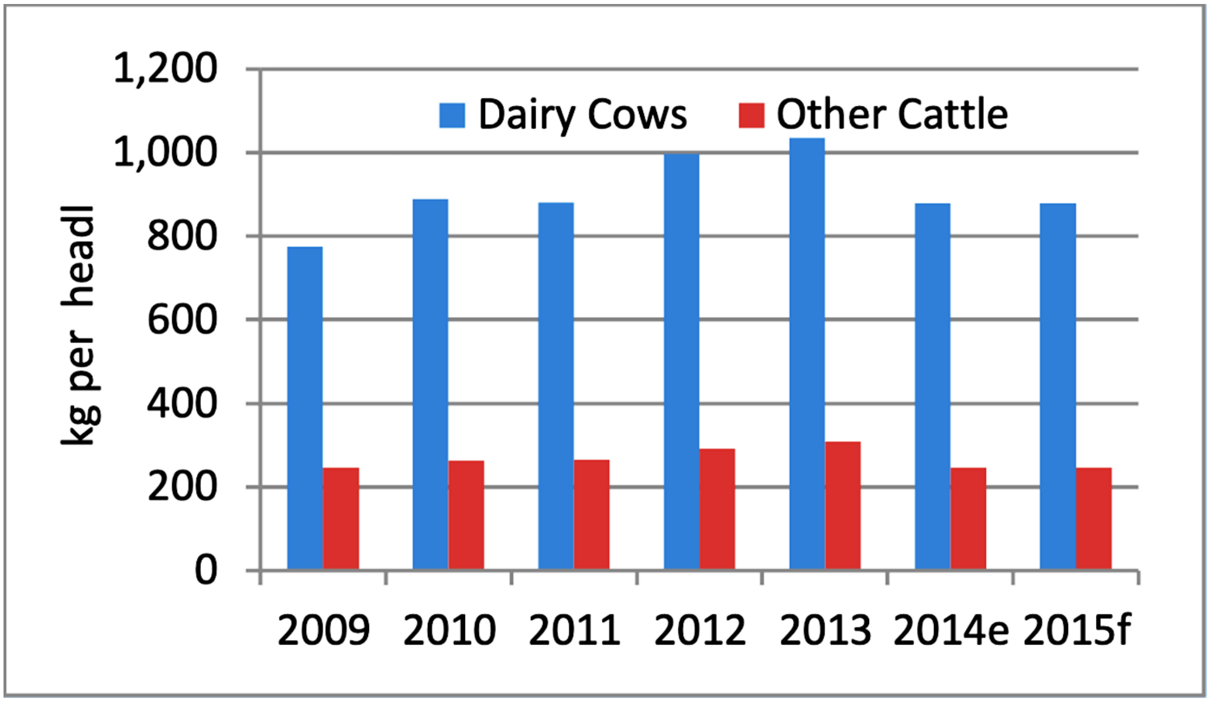


Figure 7.2. Dairy and Beef Feed Use 2009 – 2015. Source: Teagasc Situation and Outlook, 2015 (Teagasc, 2016)

If we focus on a specific agricultural sector, such as the dairy enterprise, as outlined in the 2015 Situation and Outlook report, valuable insights emerge. For instance, fertilizer use, which had experienced a significant increase in 2013 following the fodder crisis, saw a decline of 6 percent in 2014. Additionally, prices are estimated to have decreased by 8 percent in 2014 compared to the levels in 2013. The combined effect of reduced usage and lower prices is projected to have led to a 14 percent decrease in fertilizer expenditure.

Figure 7.3, extracted from the dairy sector's 2015 Situation and Outlook annual review report, portrays the average total milk production costs from 2003 to 2015 in euro cents per litre. The visual representation underscores that the primary contributors to the cost of milk production include pasture and forage, labor, and other fixed or overhead costs. The researchers anticipate a slight reduction in milk production in 2015 compared to 2014.

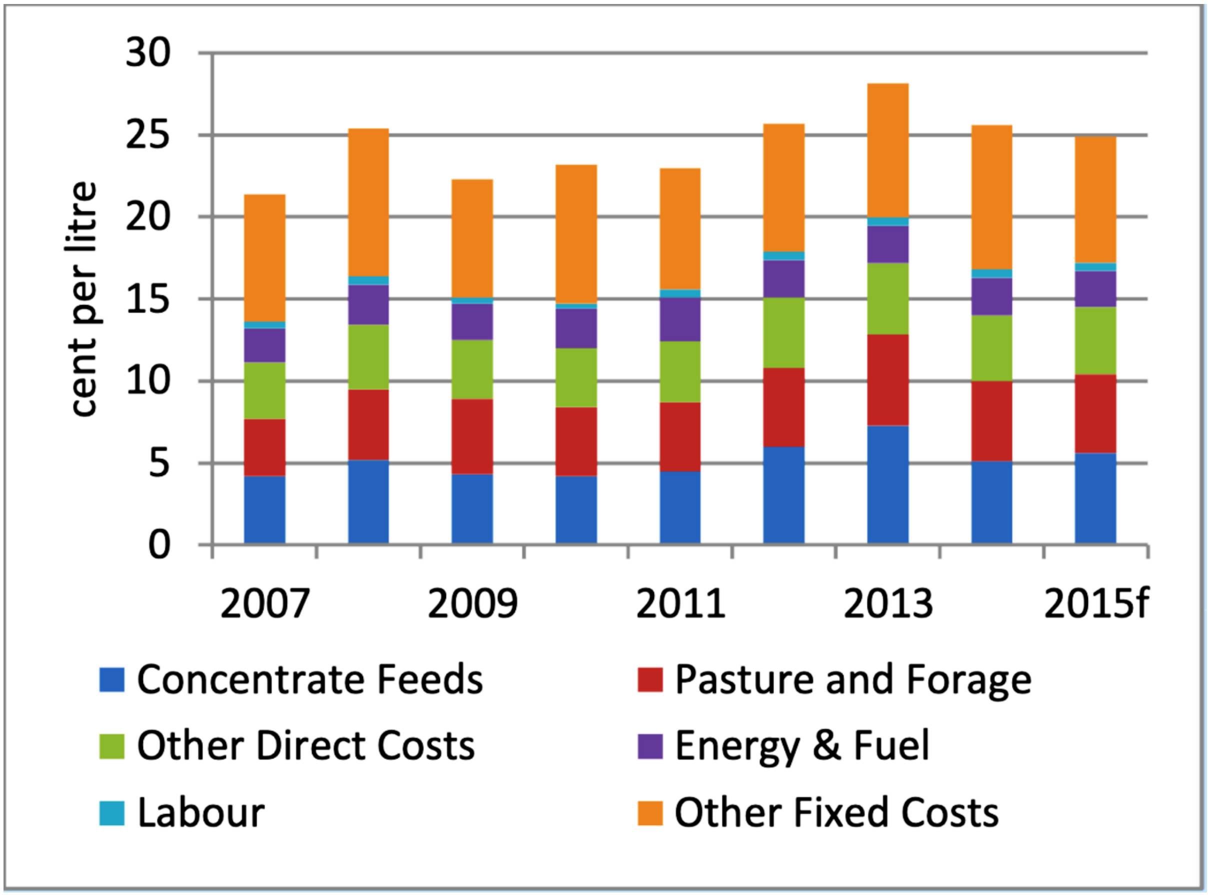
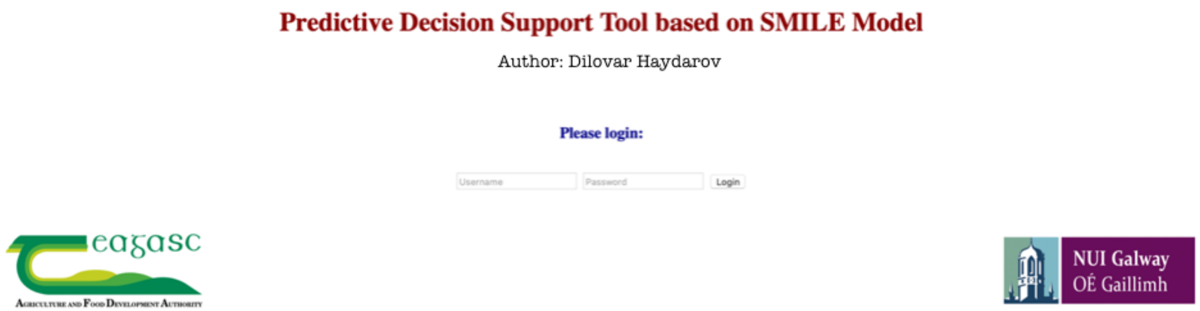


Figure 7.3. Average Total Milk Production Costs (cent per litre) in Ireland: 2003 to 2015.

Source: Teagasc Situation and Outlook, 2015 (Teagasc, 2016)

7.3.2.3. Decision Support Tool and Visualisation

The Decision Support Tool created in this study was introduced through an online accessible web platform hosted on a free Salesforce.com, Inc. server with limited technical performance. Access to this platform was granted through a login and password, which could be provided to farmers and other interested parties. Figure 7.4 displays the primary landing webpage of the Decision Support Tool, and the most recent accessibility of the main webpage was recorded in August 2021 via the link: https://teagasc-nuig.herokuapp.com. Additional details about the tool can be found in figures 7.6-7.12 in the appendix.



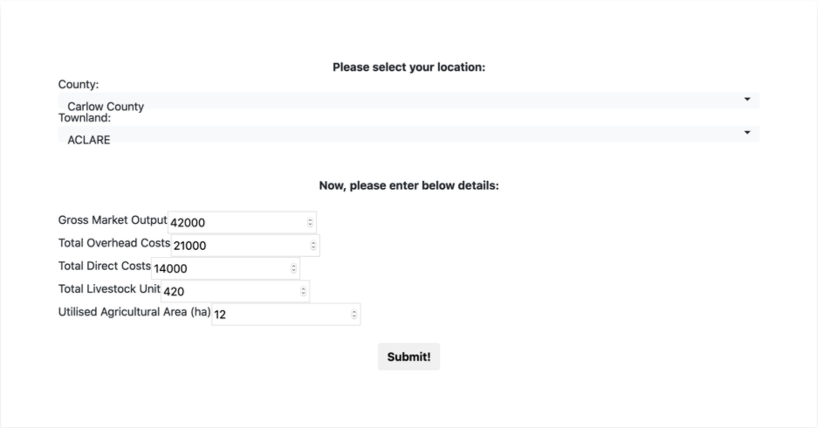
Predictive Decision Support Tool based on SMILE Model

Author: Dilovar Haydarov

Please login:

Figure 7.4. Main landing webpage of Decision Support Tool. Source: Produced by Authors.

Figure 7.5 displays a webpage where users are required to enter basic farm-related information, such as location, utilized agricultural area, farm overhead and direct costs, livestock unit, and gross market output. This information is then used to generate and provide a benchmark information report through the Decision Support Tool. Since this web tool is hosted on a free server, it may experience slow loading times and occasional errors. In such cases, users are advised to attempt submitting their information a second time.



Please select your location:

County:
Carlow County

Townland:
ACLARE

Now, please enter below details:

Gross Market Output 42000
Total Overhead Costs 21000
Total Direct Costs 14000
Total Livestock Unit 420
Utilised Agricultural Area (ha) 12

Figure 7.5. Input page of Decision Support Tool. Source: Produced by Authors.

7.4. Results

Figures 7.6 and 7.7 in the appendix depict a hypothetical farm with identical characteristics (including gross market output, farm overhead and direct costs, livestock unit, and utilized agricultural area) situated in different locations: one in the South-East of Ireland and the other in the West of the country. Despite sharing the same farm attributes, the diverse geographical locations lead to distinct benchmark classifications in terms of output, profit, and costs. For example, the first farmer (Figure 7.6) falls within the middle category for overhead costs and net profit, while the second farmer (Figure 7.7) is positioned at the top in overhead costs but at the bottom in net farm profit. This highlights the importance of localized and farm-specific information, where a farm's physical location plays a crucial role as it reflects specific land soil characteristics, rainfall, temperature, and altitude, thereby influencing farm output, costs, and profit.

Table 7.2 shows the examination of the effects of using the average price index simulated for year-to-year changes, and it is not the actual changes that differ from one farm to another. Market output and direct costs exert a greater influence compared to farm income, which relies more on subsidies and therefore lessens the impact. Also, there is increased variation among terciles, with the lower terciles experiencing the most significant effects. At the farm level, the impact on direct costs is more pronounced than on market output.

If look at the farm level values, the tercile 1 shows negative values across all categories (-0.07 for gross output, -0.11 for direct costs, and -0.04 for overhead costs), while the 2nd tercile has marginal values close to zero (-0.01 for both gross output and direct costs, and 0.01 for overhead costs). The 3rd tercile also presents small negative values, -0.02 for gross output, -0.03 for direct costs, and no change for overhead costs, and the total farm level values for all terciles combined are -0.02 for gross output, -0.03 for direct costs, and 0.00 for overhead costs.

Table 7.2. Impact of Heterogeneous Price Changes

Gross Margin Tercile	Gross Margin	Market Output	Direct Costs	Overhead Costs
1	-0.09	-0.07	-0.11	-0.04
2	0.12	-0.01	-0.01	0.01
3	-0.03	-0.02	-0.03	0
Total	-0.05	-0.02	-0.03	0
		Cattle GO	Sheep GO	Crops GO
1	0.03	0	-0.04	-0.17
2	0.04	0.01	-0.04	-0.09

3	0.20	0.08	-0.01	-0.16
Total	0.13	0.05	-0.03	-0.15
		Cattle DC	Sheep DC	Crops DC
1	0.03	0.01	-0.16	0.03
2	-0.01	-0.01	-0.04	0.03
3	-0.02	-0.03	-0.03	-0.06
Total	-0.01	-0.02	-0.06	-0.04

Note: This table values are based on 2014 year. Source: Produced by Authors.

Table 7.3 presents randomly chosen county-level average farm values for eight regions from the NFS dataset. The rightmost columns show the individual farm-level impact of heterogeneous price fluctuations. In contrast to overall country-level impact values as per Table 7.2, Tables 7.3-7.5 demonstrate specific location-based price change coefficients of farms, which can be helpful for the analysis of individual farms by farmers and agricultural policymakers. The base price change coefficients are calculated from the median (2nd) tercile and adjusted per gross margin from Table 7.2. These figures for gross output, overhead, and direct costs demonstrate that lower-level spatial financial information can be more representative of a farm within a county, as opposed to regional or national-level data. Since this lower-level data may be more relevant to farmers, it could further enhance their engagement in financial planning.

Table 7.3. Randomly chosen county level aggregates per each NFS region

									Impact of Heterogeneous Price Changes			
Region	County	Electoral District	Townland	Year	Gross Output	Overhead Costs	Direct Costs	Gross Margin	Gross Output	Overhead Costs	Direct Costs	Gross Margin
Region 1	Donegal	Rathmelton	Aughnish isle	2007	51721	18968	17583	15171	0.002	0.001	-0.002	-0.024
Region 2	Dublin	Swords-Lissenhall	Magillstown	2013	85586	32012	29605	23969	-0.004	-0.005	0.004	0.031
Region 3	Wicklow	Imael South	Ballytoole lower	2005	74040	25135	26265	22640	-0.002	-0.002	0.002	0.023
Region 4	Longford	Ballymahon	Cloonkeen	2005	44408	15986	15197	13225	0.003	0.002	-0.003	-0.036
Region 5	Limerick	Ardpatrick	Baunmore	2008	68718	21915	24616	22188	-0.001	0.000	0.001	0.020
Region 6	Carlow	Corries	Heath	2009	77388	27868	26915	22605	-0.002	-0.003	0.002	0.022
Region 7	Cork	Rathluirc	Ballysallagh	2003	82135	26646	29286	26203	-0.003	-0.003	0.003	0.045
Region 8	Galway	Dunmore North	Carrowmanagh	2013	44786	16328	15255	13203	0.003	0.002	-0.003	-0.036

Source: Produced by Authors.

Like Table 7.3, Tables 7.4 and 7.5 showcase randomly chosen average farm values at the electoral district and townland levels. These tables offer even more detailed spatial information compared to the county level, bringing them closer to actual farm-level values. In addition to the proximity of this financial information to real farms in specific locations, the data from the Decision Support Tool can assist farmers with low engagement in financial planning. It enables them to benchmark their own performance against others in their county, electoral district, and townland, providing a clearer understanding of how their financial performance compares locally.

Table 7.4. Randomly chosen electoral district level aggregates per each NFS region

									Impact of Heterogeneous Price Changes			
Region	County	Electoral District	Townland	Year	Gross Output	Overhead Costs	Direct Costs	Gross Margin	Gross Output	Overhead Costs	Direct Costs	Gross Margin
Region 1	Donegal	Rathmelton	Aughnish isle	2007	72849	22280	26229	24340	-0.001	0.000	0.002	0.030
Region 2	Dublin	Swords-Lissenhall	Magillstown	2013	141618	56128	51100	34390	-0.012	-0.016	0.013	0.091
Region 3	Wicklow	Imael South	Ballytoole lower	2005	73031	23343	27454	22234	-0.002	-0.001	0.002	0.017
Region 4	Longford	Ballymahon	Cloonkeen	2005	45591	15454	15720	14417	0.003	0.003	-0.003	-0.030
Region 5	Limerick	Ardpatrick	Baunmore	2008	89718	29781	31830	28106	-0.004	-0.004	0.004	0.052
Region 6	Carlow	Corries	Heath	2009	82237	24380	32305	25552	-0.003	-0.001	0.005	0.037
Region 7	Cork	Rathluirc	Ballysallagh	2003	98761	31156	33616	33989	-0.006	-0.004	0.005	0.088
Region 8	Galway	Dunmore North	Carrowmanagh	2013	35943	13731	12251	9962	0.004	0.004	-0.004	-0.057

Source: Produced by Authors.

Table 7.5. Randomly chosen townland level aggregates per each NFS region

									Impact of Heterogeneous Price Changes			
Region	County	Electoral District	Townland	Year	Gross Output	Overhead Costs	Direct Costs	Gross Margin	Gross Output	Overhead Costs	Direct Costs	Gross Margin
Region 1	Donegal	Rathmelton	Aughnish isle	2007	223400	53663	73765	95972	-0.026	-0.020	0.016	0.607
Region 2	Dublin	Swords-Lissenhall	Magillstown	2013	99938	43321	33392	23225	-0.006	-0.014	0.002	0.058
Region 3	Wicklow	Imael South	Ballytoole lower	2005	74784	24966	24238	25581	-0.002	-0.004	-0.001	0.075
Region 4	Longford	Ballymahon	Cloonkeen	2005	45456	15224	14754	15478	0.003	0.001	-0.005	-0.001

Region 5	Limerick	Ardpatrick	Baunmore	2008	188832	61599	61873	65361	-0.021	-0.025	0.012	0.376
Region 6	Carlow	Corries	Heath	2009	68026	9886	29571	28569	-0.001	0.004	0.001	0.098
Region 7	Cork	Rathluirc	Ballysallagh	2003	101413	41003	31159	29251	-0.007	-0.013	0.001	0.103
Region 8	Galway	Dunmore North	Carrowmanagh	2013	35837	11326	14952	9559	0.004	0.004	-0.005	-0.046

Source: Produced by Authors.

Table 7.6 presents detailed financial information on agricultural outputs and costs across various counties in Ireland. Each row corresponds to a specific county, providing insights into four key financial metrics: gross output, overhead costs, direct costs, and net profit. Gross output signifies the total revenue generated by the farms in each county, showcasing significant variations and indicating diverse scales and productivity levels of agricultural operations. For instance, counties Cork and Wexford exhibit high gross outputs of €82,381.91 and €91,995.26, respectively, suggesting more extensive or higher-value farming activities compared to counties like Leitrim and Mayo, where the gross outputs are considerably lower at €39,212.12 and €40,543.25.

The columns for overhead costs and direct costs outline the expenses associated with farming in each county. Overhead costs encompass ongoing operational expenses like maintenance, utilities, and administrative costs, while direct costs include expenses directly tied to farming activities, such as seed, feed, and labor costs. Subtracting these costs from the gross output determines the net profit, representing the actual earnings of the farms after accounting for all expenses. Net profit values shed light on the economic health and viability of farming in each county. For instance, counties like Cork and Wexford demonstrate relatively robust net profits of €26,458.14 and

€27,789.46, respectively, indicating profitable farming sectors. In contrast, counties with lower net profits, such as Leitrim and Mayo, may suggest challenges in either lower revenue generation, higher relative costs, or a combination of both. The table also includes average values across all counties, providing a benchmark for comparing individual county performance against the broader regional trend.

Table 7.6. Descriptive statistics of model variables

County	Gross Output (€)	Overhead Costs (€)	Direct Costs(€)	Net Profit (€)
Carlow	77621.48	27951.68	26861.21	22808.6
Cavan	49096.17	16929.29	17202.83	14964.06
Clare	47865.14	16606.58	16712.67	14545.89
Cork	82381.91	26726.02	29197.74	26458.14
Donegal	51618.46	18948.79	17618.33	15051.34
Dublin	77316.8	28936.65	26411.85	21968.29
Galway	44652.27	16294.71	15300.88	13056.68
Kerry	60134.58	20184.35	21144.05	18806.18
Kildare	77400.24	27883.87	26793.42	22722.95
Kilkenny	84073.5	27515.23	29993.63	26564.64
Laois	71023.6	24371.17	24900.21	21752.22
Leitrim	39212.12	14771.27	13343.15	11097.7
Limerick	68741.95	21915.73	24561.84	22264.38
Longford	44275.11	15937.88	15242.76	13094.47
Louth	77703.61	28398.92	26735.24	22569.45

Mayo	40543.25	15077.43	13957.61	11508.21
Meath	71980.4	24749.94	25069.63	22160.82
Monaghan	46848.07	16270.95	16549.44	14027.68
Offaly	65166.18	22237.56	23074.29	19854.33
Roscommon	41803.15	15445.31	14290.29	12067.54
Sligo	43678.88	16105.36	15135.99	12437.53
Tipperary	79716.54	25667.71	28466.87	25581.96
Waterford	84809.56	27367.26	30433.13	27009.18
Westmeath	58279.96	20012.91	20374.78	17892.27
Wexford	91995.26	31867.2	32338.6	27789.46
Wicklow	74187.68	25185.05	26213.08	22789.55
Total	62020.76	21299.19	21740.84	18980.73

Source: Produced by Authors.

7.5. Discussion and Conclusions

The primary aim of this project is to develop scientific tools for constructing a farm-level financial information system that can significantly enhance decision-making on farms. Using the outputs of this project, farmers can improve their profitability and environmental performance via improved cost management which has been achieved using comparison and comparative methods with more technically effective peers. In order to identify areas for improvement, this requires a systematic evaluation of operating costs and effectiveness metrics. In addition, it is essential to make well informed decisions about optimum animal stock levels in order to ensure a more coherent and effective approach to farming that balances sustainability with profitability.

The adoption of particular farm systems that best comply with their capacities, available land and funding requirements can help farmers optimise their operations in order to increase the total amount of productivity. Another critical aspect contributing to increased crop yields and promoting sustainability farming practices through minimising environmental impact is the focus on management of nutrients. In order to promote overall resilience and success in agriculture enterprises, it is essential that investment decisions be made with due regard for the long-term objectives as well as a rigorous evaluation of their compatibility.

The project emphasizes the importance of predictive and real-time data related to feed requirements and availability at a localized level throughout the year. This data enables extension advisors to provide targeted advice and establish early warning systems during challenging periods. It facilitates the prioritization of resources based on spatial considerations and enhances the advisors' ability to deliver localized agronomic guidance and planning recommendations to farmers, addressing specific challenges faced in different regions.

The project's contributions extend beyond the immediate benefits to farmers. Firstly, it enables more accurate estimates of soil moisture, as demonstrated by the Irish meteorological service. Secondly, it provides policymakers with a better understanding of the impact of improved financial management. Lastly, the information contributes to the effective dissemination of crucial financial planning messages across diverse stakeholders, fostering a more informed and responsive agricultural ecosystem.

The involvement of agricultural extension specialists within the project team is crucial for maximizing impact. Their deep understanding of how farmers interact with and respond to information is vital in comprehending the behavioral processes underpinning farmer decision-making. To ensure effectiveness, the outputs from the decision support tool need to be presented in a manner that is easily understandable and usable by farmers, irrespective of their varying levels of technical proficiency.

The project's unique contribution to academic literature lies in its utilization of big data. While big data has been extensively used in precision agriculture for making agronomic decisions, the project's innovation lies in applying real-time decision tools focused on predictive, full-farm financial benchmarking. These tools leverage real-time administrative and satellite data, representing a new frontier in the field.

DATA AVAILABILITY

To access the data used to support the findings of this study, Teagasc - the Agriculture and Food Development Authority should be contacted at https://www.teagasc.ie/rural-economy/rural-economy/national-farm-survey/.

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AUTHORS CONTRIBUTION

Dilovar Haydarov: writing the paper, analysis, developing the tool.

Chaosheng Zhang: minor revision of the paper.

Cathal O'Donoghue: general advice.

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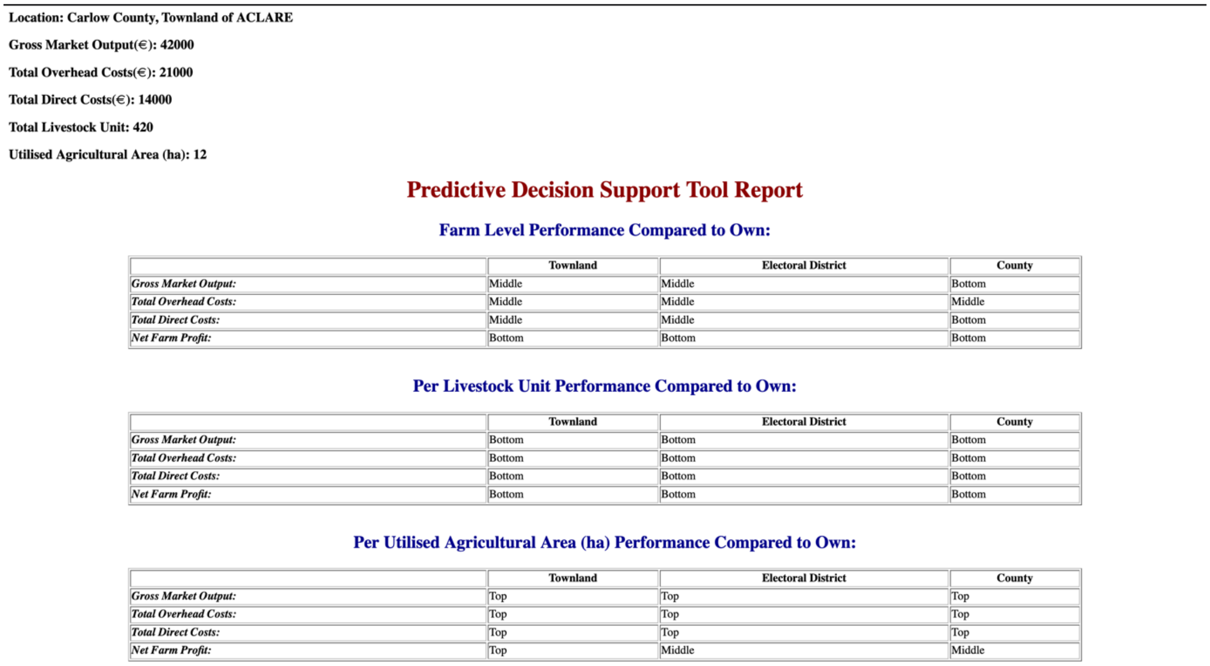
APPENDIX



Location: Carlow County, Townland of ACLARE

Gross Market Output(€): 42000

Total Overhead Costs(€): 21000

Total Direct Costs(€): 14000

Total Livestock Unit: 420

Utilised Agricultural Area (ha): 12

Predictive Decision Support Tool Report

Farm Level Performance Compared to Own:

	Townland	Electoral District	County
Gross Market Output:	Middle	Middle	Bottom
Total Overhead Costs:	Middle	Middle	Middle
Total Direct Costs:	Middle	Middle	Bottom
Net Farm Profit:	Bottom	Bottom	Bottom

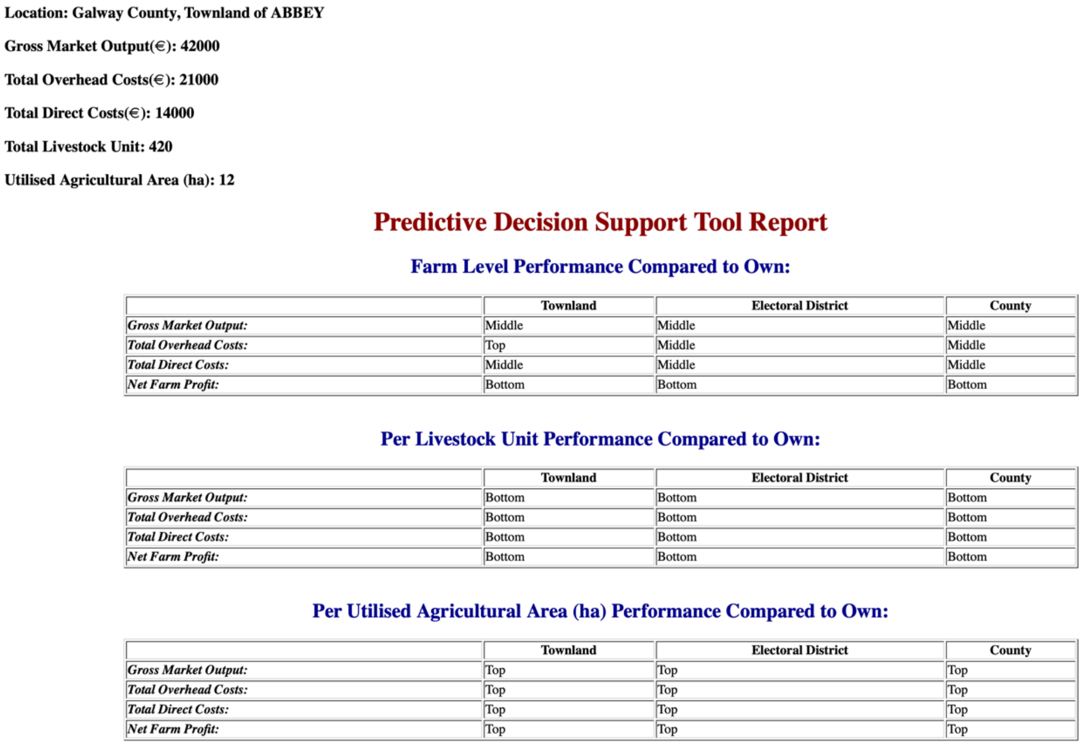
Per Livestock Unit Performance Compared to Own:

	Townland	Electoral District	County
Gross Market Output:	Bottom	Bottom	Bottom
Total Overhead Costs:	Bottom	Bottom	Bottom
Total Direct Costs:	Bottom	Bottom	Bottom
Net Farm Profit:	Bottom	Bottom	Bottom

Per Utilised Agricultural Area (ha) Performance Compared to Own:

	Townland	Electoral District	County
Gross Market Output:	Top	Top	Top
Total Overhead Costs:	Top	Top	Top
Total Direct Costs:	Top	Top	Top
Net Farm Profit:	Top	Middle	Middle

Figure 7.6. A hypothetical farm in townland of Aclare, County Carlow. Source: Produced by Authors.



Location: Galway County, Townland of ABBEY

Gross Market Output(€): 42000

Total Overhead Costs(€): 21000

Total Direct Costs(€): 14000

Total Livestock Unit: 420

Utilised Agricultural Area (ha): 12

Predictive Decision Support Tool Report

Farm Level Performance Compared to Own:

	Townland	Electoral District	County
Gross Market Output:	Middle	Middle	Middle
Total Overhead Costs:	Top	Middle	Middle
Total Direct Costs:	Middle	Middle	Middle
Net Farm Profit:	Bottom	Bottom	Bottom

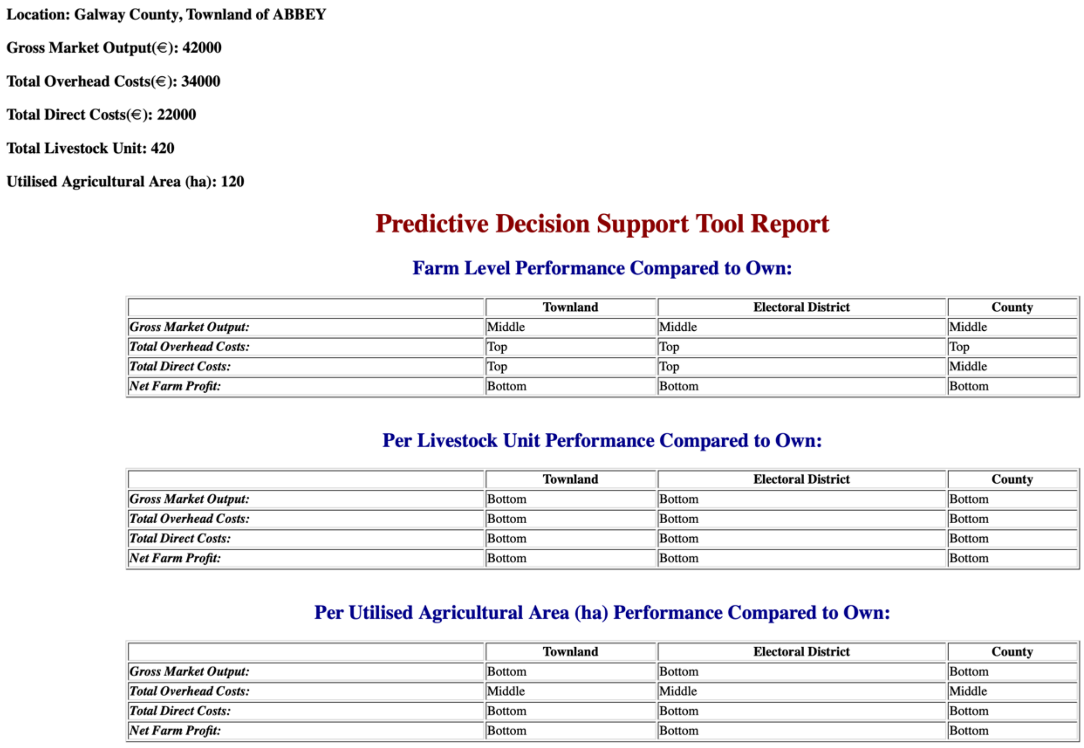
Per Livestock Unit Performance Compared to Own:

	Townland	Electoral District	County
Gross Market Output:	Bottom	Bottom	Bottom
Total Overhead Costs:	Bottom	Bottom	Bottom
Total Direct Costs:	Bottom	Bottom	Bottom
Net Farm Profit:	Bottom	Bottom	Bottom

Per Utilised Agricultural Area (ha) Performance Compared to Own:

	Townland	Electoral District	County
Gross Market Output:	Top	Top	Top
Total Overhead Costs:	Top	Top	Top
Total Direct Costs:	Top	Top	Top
Net Farm Profit:	Top	Top	Top

Figure 7.7. A hypothetical farm A in townland of Abbey, County Galway. Source: Produced by Authors.



Location: Galway County, Townland of ABBEY

Gross Market Output(€): 42000

Total Overhead Costs(€): 34000

Total Direct Costs(€): 22000

Total Livestock Unit: 420

Utilised Agricultural Area (ha): 120

Predictive Decision Support Tool Report

Farm Level Performance Compared to Own:

	Townland	Electoral District	County
Gross Market Output:	Middle	Middle	Middle
Total Overhead Costs:	Top	Top	Top
Total Direct Costs:	Top	Top	Middle
Net Farm Profit:	Bottom	Bottom	Bottom

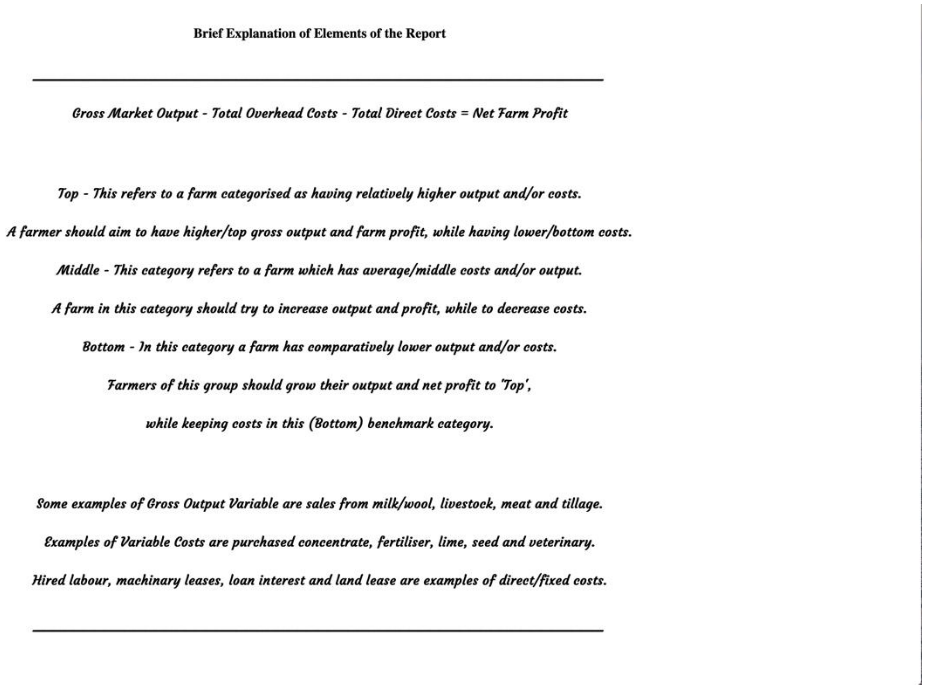
Per Livestock Unit Performance Compared to Own:

	Townland	Electoral District	County
Gross Market Output:	Bottom	Bottom	Bottom
Total Overhead Costs:	Bottom	Bottom	Bottom
Total Direct Costs:	Bottom	Bottom	Bottom
Net Farm Profit:	Bottom	Bottom	Bottom

Per Utilised Agricultural Area (ha) Performance Compared to Own:

	Townland	Electoral District	County
Gross Market Output:	Bottom	Bottom	Bottom
Total Overhead Costs:	Middle	Middle	Middle
Total Direct Costs:	Bottom	Bottom	Bottom
Net Farm Profit:	Bottom	Bottom	Bottom

Figure 7.8. A hypothetical farm B in townland of Abbey, County Galway. Source: Produced by Authors.



Brief Explanation of Elements of the Report

Gross Market Output - Total Overhead Costs - Total Direct Costs = Net Farm Profit

Top - This refers to a farm categorised as having relatively higher output and/or costs.

A farmer should aim to have higher/top gross output and farm profit, while having lower/bottom costs.

Middle - This category refers to a farm which has average/middle costs and/or output.

A farm in this category should try to increase output and profit, while to decrease costs.

Bottom - In this category a farm has comparatively lower output and/or costs.

Farmers of this group should grow their output and net profit to 'Top',

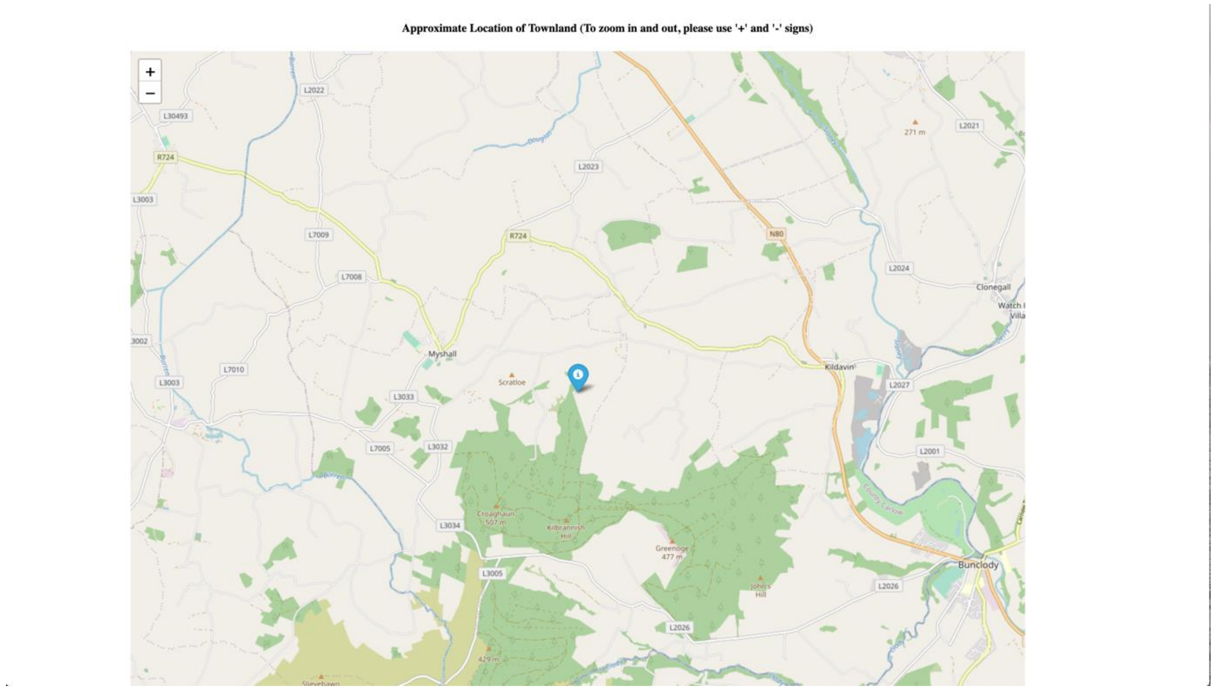
while keeping costs in this (Bottom) benchmark category.

Some examples of Gross Output Variable are sales from milk/wool, livestock, meat and tillage.

Examples of Variable Costs are purchased concentrate, fertiliser, lime, seed and veterinary.

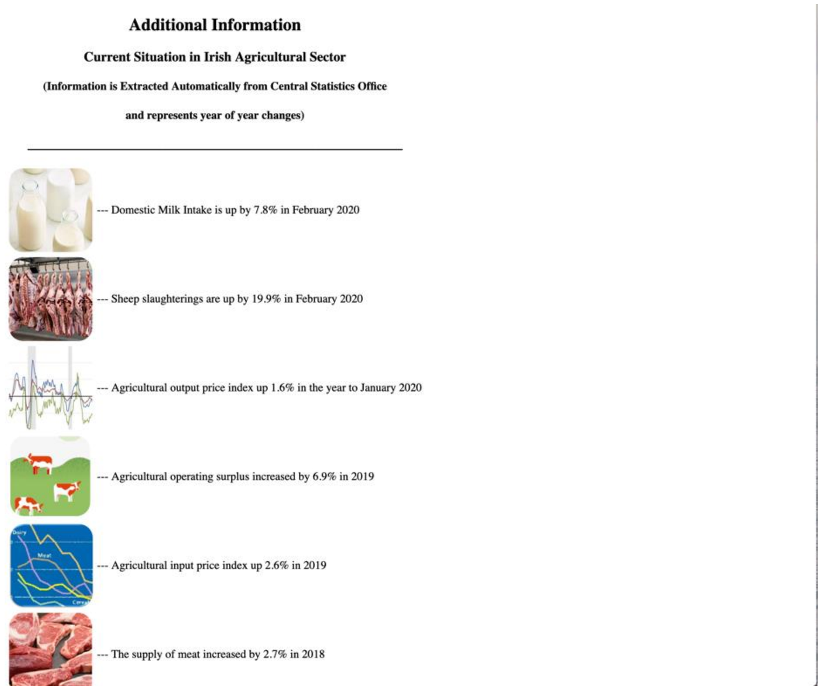
Hired labour, machinary leases, loan interest and land lease are examples of direct/fixed costs.

Figure 7.9. A brief description of Decision Support Tool's additional information. Source: Produced by Authors.



Approximate Location of Townland (To zoom in and out, please use '+' and '-' signs)

Figure 7.10. Location of a Hypothetical Farm. Source: Produced by Authors.



Additional Information

Current Situation in Irish Agricultural Sector

(Information is Extracted Automatically from Central Statistics Office

and represents year of year changes)

--- Domestic Milk Intake is up by 7.8% in February 2020

--- Sheep slaughterings are up by 19.9% in February 2020

--- Agricultural output price index up 1.6% in the year to January 2020

--- Agricultural operating surplus increased by 6.9% in 2019

--- Agricultural input price index up 2.6% in 2019

--- The supply of meat increased by 2.7% in 2018

Figure 7.11. Additional Information of Current Situation in Irish Agri-Sector (part 1). Source: Produced by Authors.

--- Area under cereals down 6.4% in June 2019

--- Number of Cattle down 139,900 (-1.9%) in June 2019

--- Cereal Production up 29.3% in 2019

--- Sheep Numbers up 2.9% in December 2019

For any queries, please contact: dilovar.haydarov@teagasc.ie or dilovar.haydarov@nuigalway.ie

Figure 7.12. Additional Information of Current Situation in Irish Agri-Sector (part 2). Source: Produced by Authors.

8. CHAPTER EIGHT: Discussion and conclusions

The final chapter of the thesis will provide a summarized discussion and concluding remarks. This chapter consists of five sections.

8.1. Important Findings and Contributions

The study of thesis aimed to assess how localized agronomic and environmental factors impact farms using a farm-level spatial microsimulation model called and developed SMILE-Env (SMILE - Environment). By integrating these variables into the model, the researchers compared results from scenarios with and without considering agronomic variations. The findings indicated that incorporating localized agronomic and environmental data improved the accuracy of the farm spatial microsimulation model, highlighting the importance of including such factors in farm-level models for better precision.

This research contributes to enhancing decision-making on farms by developing tools for a farm-level financial information system. By analyzing operating costs, effectiveness metrics, and optimal animal stock levels, farmers can improve profitability and environmental performance through better cost management practices. Tailoring farm systems to individual capacities, available resources, and funding requirements can optimize productivity while promoting sustainable farming practices like nutrient management.

The project emphasizes the significance of real-time localized data on feed requirements for providing targeted advice to farmers throughout the year. This data aids in resource prioritization, enhances agronomic guidance delivery, and establishes early warning systems during challenging periods. Beyond benefiting farmers directly, the project also provides valuable insights for policymakers on financial management impacts and facilitates the dissemination of financial planning messages across agricultural stakeholders.

Involving agricultural extension specialists is crucial for maximizing project impact by understanding farmer decision-making processes and tailoring decision support tools to be user-friendly. The project's innovative use of big data focuses on real-time full-farm financial benchmarking tools, utilizing administrative and satellite data for predictive decision-making in agriculture, marking a significant advancement in the field.

Furthermore, different regions in the country exhibit varying economic, behavioral, and biological drivers that influence farmers' decisions. Commercial farmers in areas with better land tend to rely more on farming for income, leading to a stronger focus on farm management and improvement due to higher commercial returns. This heightened behavioral attitude results in increased intention to follow lime application advice for soil pH stabilization. While the economic benefits of lime application are well-documented, not all farmers adhere to these recommendations, highlighting the interplay between behavioral and economic factors in lime application practices.

This study delves into the spatial distribution of attitudes, subjective norms, perceived resources, perceived behavioral controls, and intentions related to lime application. It assesses the various factors influencing farmers' intentions to lime their land and analyzes the economic aspects such as the cost and net benefits of lime application. Farmers' attitudes are shown to vary spatially based on past experiences and knowledge of lime practices, emphasizing the importance of attitude in influencing behavioral intentions.

Perceived behavioral control, another key aspect of the theory of planned behavior, demonstrates a geographically diverse impact on farmers' intentions regarding lime application. This perception reflects farmers' confidence in understanding and implementing lime recommendations. While limited literature directly links perceived behavioral control to lime application, existing research supports its role in influencing intentions across different contexts.

Subjective norms, representing social codes of behavior within a community, also play a significant role in farmers' intentions towards lime application, with varying effects observed across different regions. These norms can differ based on customary or group influences, contributing to spatial variations in farmers' attitudes towards lime application. Previous studies have shown that subjective norms can significantly influence attitudes and intentions in various contexts, underscoring their importance in shaping behavior.

The variable of perceived resources, a component of the extended theory of planned behavior as discussed by Zeweld et al. (2017), focuses on factors like financial resources, labor, and time within the framework of planned behavior theory. This study reveals that perceived resources, like other variables in the theory, exhibit spatial variability and have diverse geographical impacts across regions. This spatial diversity suggests that farmers possess varying financial and labor resources across different locations, influencing their willingness to adopt lime application recommendations. Previous research by Daxini et al. (2018) indicates a positive and significant association between perceived resources and farmers' intentions to implement nutrient management planning practices.

Geographically weighted regression results indicate distinct spatial patterns for farm direct and overhead costs, suggesting that these two types of costs affect farmers' intentions to stabilize soil pH levels differently. For example, in the North region, overhead costs are negatively correlated with farmers' intention to lime, while direct costs show a positive relationship in the same region. This finding has significant implications for researchers and policymakers considering research and policy initiatives related to lime nutrient management planning costs. While lime application costs are extensively discussed in various contexts in the literature, the specific relationship between liming costs and farmers' behavioral intentions has not been thoroughly explored.

Farmers consider lime and application costs crucial factors when deciding whether to follow lime recommendations. The estimated spatial distribution of required liming costs to stabilize soil pH levels (6.3-7.0) reveals varying financial burdens across regions, with some areas needing substantial investments to neutralize soil acidity while others require minimal or no cost due to already adequate pH levels. Calculating the cost of liming necessary for pH level balance can serve as a valuable tool for policymakers and researchers in cost analysis and policy development related to nutrient management planning.

The net benefit of liming, calculated as the total benefit minus the total costs of lime application in this study, serves as an incentive for farmers to adhere to lime recommendations by providing insight into potential gains from stabilizing soil pH levels and enhancing macronutrient absorption. Farm advisors can utilize these findings to offer location-specific recommendations to farmers, while policymakers can base lime nutrient management policies on pre-analysis of financial gains per hectare.

In conclusion, this study can serve as a benchmark for researchers conducting lime and nutrient management planning studies and provide policy guidance for policymakers initiating nutrient management planning strategies. Irish farmers and advisors can use this research as foundational knowledge to comprehend spatial lime practices, behavioral aspects of lime application, and the costs and benefits of soil pH stabilization. Furthermore, the study contributes to the literature on the theory of planned behavior and lime nutrient management planning, addressing key questions regarding farmers' intentions towards adopting lime recommendations and their spatial distribution.

Finally, being familiar with how farm investments affect farm gross output and expenses is essential for farmers and agricultural policymakers to sustain the economic sustainability of farms. With food security being a global priority and recent spikes in food prices, it is increasingly vital for farmers to carefully manage output and costs to maintain farm profitability. This research illustrates that farm investments impact both farm output and costs, with the extent of this impact differing based on the scale of farm production and expenses. Additionally, a separate study (Kirchweger et al., 2015) corroborates that farm investments lead to increased production.

It was observed that increasing investments in machinery, livestock, and buildings resulted in increased farm gross output for most gross output deciles, except for the lowest and highest gross output farms (Haydarov and Zhang, 2023). Higher gross output increases were particularly noticeable around the third and fourth deciles. Conversely, decreasing investments led to a decrease in farm gross output across all output deciles. A related research (Zdeněk and Lososová, 2020) investigated that limited investment amounts lead to elevated expenses and diminished production efficiency, culminating in an agricultural production system that lacks competitiveness.

Regarding farm direct costs, increasing investments led to an increase of more than five percent in all direct cost deciles, except for the top tenth decile. However, decreasing investments only affected certain direct cost deciles. For farm overhead costs, an investment increase in machinery, livestock, and buildings resulted in slight increases, ranging up to about three percent in overhead cost deciles, while simultaneously decreasing costs in the bottom first, second, and top tenth overhead deciles. Conversely, an investment decrease led to a decrease of approximately twenty percent in most overhead cost deciles.

Another study (Czubak et al., 2021) found that significant spending on investments, often supported by loans, results in increased expenses. However, every farm category that engaged in these investments experienced enhanced cost-effectiveness of specific inputs. Mogues et al. (2015) mention that governmental financial measures, such as subsidies or taxes, are commonly utilized to encourage changes in production behaviour by altering production costs or the revenue and profit generated from production by the individual or entity involved. The new insights from this thesis offer valuable information for farmers and farm decision-makers to better comprehend and manage agricultural investment factors related to farm gross output and costs. The findings also indicate that farms will respond differently to investments based on the scale of farm output and costs.

As outlined in the introduction of the thesis, the work of the thesis identified a gap in current farm income spatial models, noting their failure to account adequately for localized environmental and agronomic contexts. The associated research question asked: "Does localized natural capital play a role in explaining the spatial distribution of farm income?" This inquiry seeked to integrate variables such as natural resources and environmental conditions into spatial models, thereby enhancing accuracy in depicting regional farm income patterns.

The study's findings revealed strong impacts on farm income when natural capital drivers are integrated into the model. Specifically, market gross margins per hectare saw increases in the South and South-East regions. In contrast, sub-catchment level gross margins per hectare decreased notably in the Midlands and certain parts of the North. By analyzing income variations both between and within districts, the research highlights that accounting for natural capital heterogeneity exposes greater income variability, particularly at the district level. These results underscore the critical influence of natural capital on farm income and emphasize the necessity of considering localized environmental and agronomic factors in agricultural economic analyses.

Furthermore, the work of the thesis identified a lack of direct analysis regarding the impact of farm investments on both output and costs. The corresponding research question was: "Can investment in machinery, livestock, and buildings influence agricultural output and costs, and by how much?" This investigation aimed to quantify the effects of investments in farm infrastructure, offering empirical evidence to guide optimal investment strategies for maximizing productivity and efficiency.

The study showed variations in the impact of investment in machinery, livestock, and buildings on Irish farmers' gross output across different output deciles. On average, farmers from the second to the fifth gross output deciles can expect a notable increase in gross output ranging from 9% to 12.6% with a 10% increase in investments. In contrast, farmers in the first, ninth, and tenth deciles may experience a decrease in gross output, with reductions of 7.7%, 0.05%, and 3.77% respectively, if investments are increased. This discrepancy could be attributed to differing reliance on subsidies and existing investment levels among farms at the lowest and highest output levels.

Moreover, the thesis addressed the absence of literature examining the behavioral and spatial dimensions of farm nutrient management planning. The research question posed was: "What are the interactional dynamics of behavioral, spatial, and farm income variables on farm nutrient management planning, focusing on soil pH level as a case study?" This inquiry tried to uncover relationships between human behavior, spatial factors, economic variables, and nutrient management decisions, informing more effective strategies tailored to local conditions.

The findings demonstrated that there is a 79% probability that farmers who recognize the need to lime due to low soil pH will intend to apply lime. It identified several factors influencing this intention: perceived behavioral controls, subjective norms, and perceived resources positively affect farmers' likelihood to apply lime. Surprisingly, farmers' attitudes towards lime application showed a negative correlation with their intention to lime. Additionally, higher levels of formal education, such as college degrees or professional diplomas, significantly increased farmers' inclination to apply lime. Furthermore, age categories demonstrated an inverse relationship, with younger farmers showing a higher intention to implement lime nutrient management practices compared to older farmers.

Finally, the thesis identified a research gap in farm financial planning, noting the lack of methodological and technical proposals to enhance farmer engagement with financial planning tools. The research question was: "How can a farm decision support tool and which parameters help increase farmers' engagement with farm financial planning, and how can this be pursued and achieved?" This investigation sought to develop practical solutions that integrate key parameters into decision support tools, aiming to improve farmer adoption and effectiveness in financial planning.

The proposed tool described in the thesis offers an advantage to farmers, and farm policymakers by providing detailed benchmarking information at the townland level, which proves more effective in enhancing financial planning among less engaged farmers compared to broader regional or national data. It simplifies the planning process by eliminating the requirement to input each financial transaction individually, making it particularly attractive to small-scale farmers and encouraging increased participation in economic planning.

Each main research question was designed not only to fill gaps in current knowledge but also to provide actionable insights that can inform policy decisions, enhance farm management practices, and contribute to sustainable agricultural development. By addressing these gaps, the studies of the thesis tried to bridge theoretical frameworks with practical applications, ultimately fostering more resilient and efficient agricultural systems.

To summarise it, the contribution can be divided into three groups of scientific contribution, methodological/modelling contribution, and policy contribution:

a) The scientific contribution in term of spatial microsimulation model (SMILE-Env), where the study developed and utilized the SMILE-Env model to assess localized agronomic and environmental factors affecting farms. It integrated these factors to improve the precision of farm spatial microsimulation, demonstrating the model's efficacy in capturing farm-level dynamics accurately.

The scientific contribution in term of spatial distribution of attitudes and behavioral factors, where the thesis investigated spatial variations in farmers' attitudes, subjective norms, perceived resources, and behavioral intentions regarding lime application. It explored how economic, behavioral, and biological drivers influence farmers' decisions, particularly in different regions, shedding light on spatial patterns of decision-making.

The scientific contribution in term of geographically weighted regression (GWR), where it applied GWR to analyze spatial patterns of farm direct and overhead costs concerning soil pH stabilization through lime application. It highlighted distinct regional impacts of costs on farmers' intentions, contributing to understanding economic influences on lime application practices.

b) The methodological or modelling contribution in the case of decision support tool and financial information systems, where the thesis developed a tool for a farm-level financial information system to enhance decision-making by analyzing operating costs and optimal resource allocation. The methodological microsimulation contribution focused on improving farm profitability and environmental sustainability through tailored farm economic management strategies.

Additionally, the thesis contributed to the modelling field by utilizing the theory of planned behavior in agriculture, where it applied the theory of planned behavior to assess factors influencing farmers' intentions towards lime application, including attitudes, subjective norms, and perceived behavioral control. It explored spatial variability in these factors and their implications for agricultural decision-making, providing a methodological framework for behavioral studies in agriculture.

Furthermore, the work of the thesis contributed in terms of geographically focused data utilization, in which it innovatively used big data and geospatial information to develop real-time farm financial benchmarking tool and predictive decision-making model. It demonstrated the utility of localized data in enhancing agronomic guidance and financial planning, contributing methodologically to precision agriculture approaches.

c) Finally, the thesis contributed to the policy field, for instance, in the area of policy implications of investment and farm gross output. It explored how farm investments impact farm gross output and costs across different deciles, informing policymakers on strategies to enhance farm economic sustainability, and highlighted the implications of investment decisions on farm competitiveness and production efficiency, guiding agricultural policies related to financial support and incentives.

It contributed to the policy field in terms of cost-benefit analysis of lime application, in which it conducted cost-benefit analysis of lime application for soil pH stabilization, offering insights into potential economic gains and financial burdens across regions. The findings provide policymakers valuable new research information for formulating nutrient management policies aimed at optimizing agricultural productivity and sustainability.

It also contributed to the policy of governmental financial measures in terms of discussing the role of governmental financial measures such as subsidies and taxes in influencing production behavior and farm profitability. It provided policy recommendations on how financial interventions can be tailored to support sustainable agricultural practices and enhance farm profitability.

8.2. Limitations of the Research

The thesis delves into four primary areas of study focusing on the localized impact of natural capital, behavioral, spatial, and economic relationships concerning lime nutrient management, the influence of farm investment factors on output and costs, and the discussion of the role of financial management tools in fostering farmer engagement in financial planning within the context of Ireland. It can be argued that these research components may be predominantly relevant to countries akin to Ireland in terms of their environment, agricultural systems, and governmental agricultural policies.

A potential limitation of the research lies in its heavy reliance on data from the National Farm Survey conducted by Teagasc. It would be beneficial to validate certain results using an alternative data source, even though a comparable high-quality dataset is currently unavailable in Ireland. Furthermore, criticism could be directed at the study for not incorporating major exogenous factors such as climate change, economic downturns, and shifts in European Union agricultural policies into its calculations to enhance the research outcomes.

An additional limitation relates to unobserved variables. To control for variables other than those already included, and thereby separate out possible confounding effects or endogeneity, robustness checks were performed. These checks involved using alternative specifications of the model, such as different sets of control variables or functional forms, to assess whether the results were sensitive to the inclusion or exclusion of specific variables. Additionally, the thesis conducted Kolmogorov-Smirnov tests to determine whether the sample, utilizing the specified variables, conforms to the expected distribution. Furthermore, the matching technique employed in the thesis facilitated the creation of comparison groups that are similar in terms of observed confounding variables. This approach helps to mitigate bias that may arise from unobserved factors, such as different farm systems and managerial capacities.

8.3.Potential Future Research Areas

The thesis investigation could be expanded to include other countries, especially those outside the European Union, to determine whether the thesis findings align with or diverge from those of other nations. Furthermore, the decision support tool developed in the thesis could be implemented by farmers, followed by a survey to assess whether their involvement in financial planning has increased. Additionally, certain sections of the thesis study, particularly chapters five and six, could be replicated in the future to verify whether the study's findings remain consistent or have evolved over time.

The work of the thesis could be improved by analyzing the role of localized environmental factors post-intervention. By conducting this analysis, researchers could assess the effectiveness of these interventions in influencing agricultural practices and outcomes. For instance, studying changes in soil health, water quality, or biodiversity after the implementation of conservation measures could provide valuable insights into the long-term impacts of policy interventions on agricultural sustainability and productivity.

Additionally, the future improvements could be done regarding the impact of agricultural investments in different farming systems. Future research could explore how investments in machinery, livestock, and buildings affect farm output and costs across various agricultural systems, especially in countries that employ intensive indoor farming methods. Comparing these impacts between outdoor and indoor farming systems could reveal unique challenges and opportunities for optimizing resource use, productivity, and profitability. Such comparative studies could inform policymakers and stakeholders about effective strategies tailored to different agricultural contexts.

To add one that, the future related improvements could be seen in the behavioral influence on nutrient management guidelines. Using a randomized control trial approach, future research could investigate how behavioral factors influence farmers' adherence to nutrient management guidelines. This future study could explore psychological and social determinants that shape farmers' decision-making processes regarding soil health and nutrient use efficiency.

Understanding these dynamics could lead to more targeted interventions and educational programs aimed at promoting sustainable agricultural practices and environmental stewardship.

Lastly, the long-term impact of user-friendly agricultural financial planning tools could be investigated. Another potential study could examine the long-term impacts of user-friendly financial planning tools on farm output and costs. By assessing how these tools facilitate decision-making and financial management over extended periods, researchers could evaluate their effectiveness in improving farm profitability, resilience to economic fluctuations, and overall financial health. Insights from such research could guide the development and adoption of accessible financial tools that support sustainable agricultural development and enhance farm viability.

8.4. Concluding Comments

The thesis uncovered several key new findings in the areas of farm income, output, costs, investment, farmer behavior, soil nutrient management planning, financial management, and farm spatial dimensions. These findings serve to enhance the existing knowledge within the research field. They will provide valuable insights for farmers, agricultural policymakers, and researchers in addressing pertinent questions they may encounter.

8.5. References

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