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A Blueprint for a Big Data Analytical Solution to Low Farmer Engagement with Financial Management

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Abstract

As the market environment for farming has become more complicated, the need for farmer engagement in financial management has increased. However, financial management decisions need to consider individual farm environmental conditions. This paper discusses the design of a new big-data based analytical solution for low farmer engagement in financial management—a Farm Financial Information System (FARMFIS). Using a pastoral based livestock system as the case study, the methodology required to develop this predictive Information System is described. Building upon real-time weather, satellite grass growth and soil information, a local setting and a bio-physical model of weather and market changes on farm level economic outcomes are utilized. The aim is to use the back-end framework described here to develop decision support tools for farmers to provide benchmark information in relation to the financial and technical attributes to a similar top, middle or bottom one-third performing farm. This information can help farmers engage more meaningfully in their own management decisions, technologies, and practices.

Keywords: big data, bio-economic modelling, decision support tools, financial management

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Introduction

The need for farmer engagement in financial management has increased as a result of greater complexity in the market environment for farming in terms of greater volatility, more complicated investment environments and viability challenges. At all levels of profitability improved financial management is required. However, farmers are more likely to take up agricultural technologies and practices than financial ones (Hennessy and Heanue 2012). Given this more complicated farm operating environment, there is a need for greater planning in order to provide greater resilience.

While much information is available to assist financial management and/or planning such as the eProfit Monitor (ePM) decision support tool (Morrow et al. 2004), take-up of such practices and technologies has been low. However, information provided by such decision support tools is essential for improved planning. Farmers using the ePM planning tool are ranked as top, middle and bottom performing farms on the basis of gross margin per hectare so that farms can benchmark their progress. This annual income measurement is strongly correlated with longer-term net profit (Teagasc 2015). While usage has increased substantially over time, only about 10,000 Irish farmers are using the eProfit Monitor, representing only a fraction of the population.

US research found that farmers “who conduct detailed financial analyses are substantially more profitable than the farmers who…did not make the calculations” (Gloy and LaDue 2003). Macken–Walsh et al. (2015) identify challenges concerning the current use of advisor managed interaction with existing decision support tools, where participation is often motivated solely by scheme incentivization, but without internalization of the information in their decision making. Further, Macken–Walsh et al. (2015) identifies that “potentially, the use of financial decision support tools may lead to ‘conscientization,' among farmers, where they come to realize the economic potential of their businesses and the potential of these tools. Dillon et al. (2008) report that 57% of Irish dairy farmers view financial management tools as time-consuming. Internationally, Gloy and LaDue (2003) found that although financial technologies were in use, they were often misunderstood and underutilized. Thus, it would appear that despite long-term benefits, farmers are reluctant to engage with financial and business planning because it is either too difficult to use or time-consuming to compile data, particularly relative to the financial return on investment on lower-income farms.

This lack of understanding and use of financial technologies is of concern within, for example, highly debt financed farm businesses where strict financial control and cash flow monitoring is essential. The net result is that farm-level financial management practices are not part of the routines of the farms’ operations, where routines are understood in the evolutionary economics sense to be ‘ways of doing and ways of determining what to do’ (Nelson and Winte 1982). Importantly, routines in a functional sense coordinate the other resources of the farm leading to their productive utilization (Dosi et al. 2000). Effectively, this means that financial tools are not part of many farmers’ management repertoires, although they need to be.

The Importance of the Environmental Context of Farms

Many livestock systems involve housing animals indoors for much of the year. For these systems, the environmental context of individual farms may not have a large impact on the economic success of the farm business. However, in pastoral (grass-based) livestock systems, environmental factors such as soil type, rainfall, soil temperature and soil moisture deficit, can have significant impacts on start and end dates of the grass-growing season, on the length of the grass-growing season, on grass yields and on soil trafficability. These impacts are compounded for farms that additionally grow their own supplementary feed requirements. All of these environmental factors vary across space, therefore, if financial management planning systems are to be meaningful, they must take this environmental and spatial variability into account.

Pastoral farming differs from most other businesses as it is context specific and spatial modelling requirements are different from other types of businesses. Thus, the modelling solution described in this paper is unique to the land-based farming context. The main technical challenges in predictive modelling of financial results are the spatial agronomic condition, the nature of farm system, including animal stocking rates and types, and the level of farm efficiency in terms of outputs and costs. Viewing spatial and government administrative data has provided solid grounding in the agronomic and system situation respectively. The remaining challenge is to model cost and production efficiency and farm subsidies, conditional upon the spatial and system situation.

A challenge then arises from the need to develop a Financial Information System (FIS) decision support tool that can give benchmark information in relation to financial and technical information that takes both the environmental context and the varying degrees of farmer engagement or skill into account. An additional challenge lies in delivering this information in a way that does not involve transaction costs that farmers perceive to be high, for example, completion of the ePM requires high-level data. Interestingly, in developing indicators of innovation on Irish tillage farms, Hennessy et al. (2013) report that while the adoption of innovative practices such as forward contracting and soil testing is highly correlated with economic performance, IT usage on farms is more widespread across farm economic performance. The motivation for farming is varied, from profitable commercial-minded farmers, to non-economically viable lifestyle farmers. Nevertheless, given the multi-faceted nature of farming and the increasingly complicated operating environment, it can be argued that it is necessary for farmers of all types to engage in more planning. While commercially focused farmers may already be more engaged in planning, using for example farm management accounts and existing decision support tools, less profitable farmers are less likely to engage. The greatest challenge, therefore, may be to provide information that is more accessible, allowing for differential farmer engagement (Oliver et al. 2012).

For lower income farmers to engage, the overhead of data collection and analysis needs to be lower than for existing decision support tools. Predictive approaches based on existing administrative and other real-time data sources can potentially allow for personalized information with lower overhead, which might enable greater usage and engagement. Of course the greater the reliance on predictive data than actual data, the lower the accuracy, but it is likely that some information, even if simulated, is better than no information.

In essence, there is a need to develop a predictive ePM that could provide simulated benchmark information for farmers in relation to the financial and technical attributes to a similar top, middle or bottom one-third performing farm. This modelling approach would counter the data-collection challenges faced by farmers in engaging with financial planning tools such as the ePM. The ability to additionally benchmark the environmental conditions of the farm would allow for a refining of the top, middle and bottom financial and technical benchmarks. This would help farmers better engage with the management decisions, technologies, and practices required for their specific spatial and environmental conditions.

Significant quantities of data are collected either for administrative purposes or utilizing remote sensing. Similarly, there are large complementary administrative spatial data assets available for use in this type of analysis. Much of the information is available to develop a predictive information system that can provide this benchmark system. However, the input of back-end statistical, spatial analysis, agricultural systems behavioral and ICT science is necessary to develop this capacity.

In order to allow farmers to engage more easily with the financial aspects of their business, it is necessary to understand the attributes of their enterprise at a local scale, with local specific agronomic drivers (such as soils, weather, altitude, etc.) and localized management decisions in relation to land base, system and stocking rate to:

- develop a bio-economic annual profit function based upon observed farm characteristics
- incorporate farm management decisions and resulting efficiency by understanding the technical and financial characteristics of top, middle and bottom farmers
- understand how to present complex financial and technical information to farmers.

This paper discusses the data elements and analytical components that form part of a blueprint design for a new Big Data based analytical solution, a Farm Financial Information System (FARMFIS), which facilitates easier engagement in financial management planning, taking individual farm locations and environmental contexts into account. We focus in particular on pastoral grass-based livestock farmers who face multiple complexities of managing the herd and a weather dependent grass crop as well as managing their interaction with the market in terms of inputs and outputs. Ireland’s mild maritime climate provides a competitive advantage in grass growth, making it the country most reliant on grass based livestock farming in the EU.

Figure 1 presents a flow diagram of the FARMFIS decision support tool. The first component is the bio-physical methodological framework for the farm financial information system. The most important time variant, agronomic driver of grass growth is weather. In order to understand the drivers of grass growth, the weather and soil parameters are extracted at grid points, equivalent to the remote sensing based grass growth measures. In order to understand the impact of differential agronomic conditions and grass growth across the country, it is necessary to link this data to farm data, management decisions and outcomes, which will then be linked to market prices to model the consequential market impact of the interaction between these bio-physical processes. Spatial microsimulation methods are utilized to create a base data set. The final stage of the system models the economic impact at farm level of biological systems on individual farms across the country at the spatial scale. To accomplish this, a bio-economic farm systems model is utilized. Our model builds on this approach by simulating economic outcomes related to animal demographics, feed supply, feed demand, imported feed, other costs and animal outputs on the spatially referenced farm and biophysical data to generate farm-level profits.

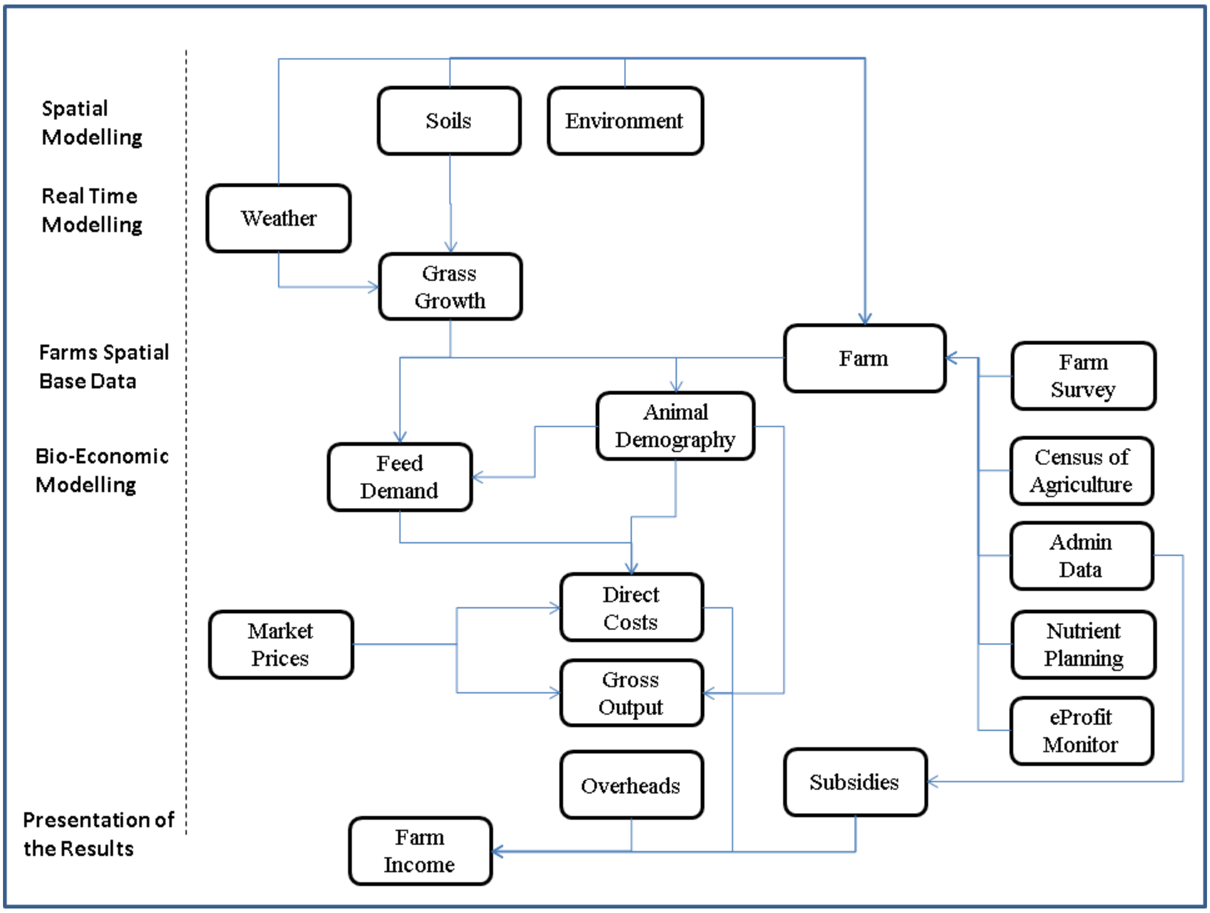

Figure 1. Structure of the FARMFIS Decision Support Tool

This paper describes a conceptual blue print for developing a decision support tool. After discussing the context in relation to the development of the model in section 2, various components of the blueprint are discussed. The bio-physical component is outlined in section 3, followed by the preparation of the base data and bio-economic system in section 4. The data requirements are charted in section 5, with a summary and next steps presented in section 6.

Extension Context

Cattle and Dairy Sector Context and Requirements of Financial Planning

Global demand for food is anticipated to increase 60% above current levels by 2020 (FAO 2015). At the same time, the increasingly international nature of food trade and associated trade policy disruptions have brought about unprecedented volatility in food prices which directly impact the financial performance of farm businesses (Shadbolt et al. 2013). Farming is widely acknowledged to be a financially risky occupation with an ever-changing landscape of possible price, yield and other outcomes that affect farm financial returns (Folke et al. 2002). Farm systems are complex and diverse, based on the resources which are unique to the farm, operating in volatile natural economic and policy circumstances. Such systems represent the collective response of farm businesses to remain viable and grow in the face of risks and uncertainties (Kaine and Tozer 2005). Due to an increasingly turbulent environment, recent studies suggest that financial evaluation of alternative farming systems must consider both the long term average profitability and the stability of farm income over time. The challenge for many farmers is to develop and implement farming systems with the preferred combination of activities and resources to mitigate these physical and financial risks and provide sustainable economic returns (Dillon et al. 2008).

For European Union (EU) dairy farmers, this challenge has been heightened in recent years due to a combination of reduced market supports and an associated increased exposure to more volatile global market prices coupled with reducing EU farm subsidies. As an export-oriented industry, the volatility of Irish dairy producer milk prices has increased four-fold during the last decade (Loughrey et al. 2015), and taken together with input price inflation, has resulted in increasingly volatile farm incomes. In an uncertain environment, improved farm financial management planning is a key attribute to helping farmers deal with future challenges and shocks (Mishra et al. 1999).

Beef production is the most widespread farm enterprise in Ireland accounting for almost 80% of the 139,000 farms in the national population and 34% of the gross output value from the agri-food sector. This output is largely generated from the suckler beef cow herd which comprises approximately half of the total number of breeding females, with the remainder originating from the dairy sector. Despite the significance of the beef sector, farm family incomes are low, with many farms operating at a loss when EU and national farm support payments are excluded. The Teagasc National Farm Survey (NFS) (Hanrahan et al. 2014), which is part of the Farm Accountancy Data Network in the EU, estimates that average farm income (including the EU direct payments and agri-environmental scheme subsidies) for suckler beef cow and beef finishing farms was €9,541 (US $12,526) and €15,667 (US $20,569) respectively, in 2013 (Hanrahan et al. 2014). The level of farm employment by the farmer and/or spouse on suckler beef and beef finishing farms is high at 56% and 47% respectively. Therefore, beef farms in Ireland are heavily reliant on EU payments, and alternative sources of income to support the farm family (Hanrahan et al. 2014).

Given the abundant availability of grazed grass as a low cost and high-quality ruminant animal feed, Irish suckler beef systems are predominantly pasture-based with the majority of cows calving in spring in order to match the onset of seasonal grass growth. The grass growing season ranges from approximately 250 days in the north-east to 330 days in the south-west with a yield difference of approximately eleven tons dry matter (t DM) per hectare, per year vs. fifteen t DM per year, respectively (Brereton 1995).

Existing Extension Support for Farm Financial Planning and Challenges

Individual farm financial appraisal and forward planning are built around initially conducting a benchmarking analysis of the farm performance at the whole farm as well as the enterprise level. The Teagasc eProfit Monitor (ePM) has built its reputation as the leading financial benchmarking analysis system available for extension services in Ireland. The ePM analysis is produced in the form of a standardized report of the farm financial output, expenses and profit for the most recently completed year of trading of the farm business. The ePM system utilizes available electronic sources for large amounts of the input data to increase the speed and accuracy of the data entry process.

Extension advisers guide farmers in the collation of the required input data but the main focus of the advisers is on ensuring the analysis is representative of actual farm financial performance and also in identifying the key efficiency decisions indicated by the analysis. As such, the analysis acts as a “health-check” to assess how the business is progressing. This helps to identify areas to concentrate on during subsequent planning and budgeting and to set the baseline for whole-farm forward financial planning.

The Teagasc Farm Business Monitoring system contains a planning / budgeting process that can be short term in the form of a one or two-year cash flow budget or alternatively a five-year financial projection can be completed to check on the long-term feasibility of planned change or investment projects. Key to the potential accuracy and credibility of this forward projection is to build on the actual farm performance ePM analysis. Robust projections for future farm output and input prices along with accurate modelling of changes in farm efficiency are also important, as the planned change is implemented and becomes imbedded in the normal running of the farm. This is particularly relevant in the case of planned investment involving scale increases or radical enterprise change. The development of a robust and validated model that can simulate possible stress-testing scenarios and greatly assist farmers and their extension advisers in assessing the risk elements associated with the proposed change.

Extension: Getting Farm Financially Fit

The development of the FARMFIS builds upon a multi-actor national extension program, "*Get Farm Financially Fit*[1]" which aims to improve financial management and business planning. A network of twenty-three extension, farming, financial, media and agribusiness organizations formed a network to have an impact in this area—recognizing the need for improved financial and business planning amongst farmers, while recognizing that (for a variety of reasons) the demand is not there. The network held a national campaign during 2015, which received significant media coverage, attracted over 1000 farmers to public meetings and has been followed by special supplements and a series of fortnightly *Get Farm Financially Fit* articles in the specialist farming media. The concept of the Financial Information System (FIS) is seen by the network as a vehicle that can assist in the campaign for improved financial and business planning.

To understand how the extension processes and activities outlined above will need to be channeled in the context of FARMFIS, it is useful to be guided by Feldman and Pentland (2003) and Pentland and Feldman (2005), understanding of routines which isolate their ostensive, performative and artefact aspects. Specifically, by identifying the performative aspects of farm financial management routines (the practices/tools that farmers actually use and how they make decisions about farm finances) and their attitudes towards such practices and decisions, extension advisers will be able to clarify how a new artefact (inputting data into, and the use of, FARMFIS) can be integrated with existing farm-level routines and knowledge, and ultimately change those routines.

Macken-Walsh et al. (2015) outline what we know from the literature and from advisory expertise in Teagasc, which extension methods and approaches have been successful in relation to understanding and influencing the performative aspects of routines around ePM. These need to be applied to the FARMFIS case and include: actively generating farmers' perceptions that FARMFIS is useful and relevant; facilitating farmers' understanding of how FARMFIS works; accommodating different levels of farmer competence; involving the spouse and other family members to increase the impact of FARMFIS on farm-level

[1]Get Farm Financially Fit: http://www.teagasc.ie/rural-economy/farm-financial-fitness/.

decision-making: building esteem and pride around the use of FARMFIS and awareness of farmers' financial sensitivities.

It is hoped that the inclusion of spatial and environmental data in the FARMFIS will improve farmer engagement in financial planning as it will allow extension initiatives such as the *Get Farm Financially Fit programme,* to present financial benchmarking information which takes specific environmental challenges into account, making it easier for farmers operating in challenging environmental conditions to have realistic and achievable benchmarks.

Bio-Physical Methodological Framework for the Farm Financial Information System

The main technical challenge in predictive modelling of financial results is the spatial agronomic condition, the nature of farm system including animal stocking rates and types, and the level of farm efficiency in terms of outputs and costs. We know from spatial and government administrative data the agronomic and system situation respectively. The remaining challenge is to model cost and production efficiency and farm subsidies, conditional upon the spatial and system situation. High quality, nationally representative survey data has enabled our teams to bridge this technical challenge.

Measurement of Grass Growth Using Remote Sensing

As grass (either as pasture or winter feed) is the main feedstuff of the temperate Atlantic dairy producing nations in Europe, it is important to understand grass production variability both spatially and temporally. From an international perspective, a recent report (CSIRO Australia 2014) from Group on Earth Observation (GEO), a global body of which Ireland and EU are members) states that: *"Currently there is no comprehensive global effort for monitoring the status and productivity of pastures and rangelands."*

Globally, estimates of tillage crop yields from satellites are common, but grass yields are less common although they are being addressed in Australia and New Zealand. An important difference between grassland yields and crop yields is that final yield information is much less important in grass than estimates of current yield. Current systems only estimate grass conditions at relatively coarse spatial dimensions (sub-regional levels) in open rangeland systems, but there has been a very recent increase in research in yield monitoring in closed paddock scale operational systems (Dusseux et al. 2015; Stafford et al. 2013). In Ireland, accurate data on actual grass yields are limited to a few sites around the country and are published as growth rates as opposed to quantities of biomass. This is partially resolved by the new PastureBase Ireland grass growth recording system (Griffith et al. 2014), which is a spatially enabled database of 300+ farmers recording weekly growth rate measurements on their farms.

Satellite systems capturing daily images of the country allow us to expand from 300 farms to propose a seamless national, per-hectare coverage of weekly growth levels in Irish pastures. The system is potentially deployable in all grass-based dairy producing regions in temperate northern Europe.

This system builds on recent work in the Spatial Analysis Group of Teagasc in both grassland monitoring through machine learning (Barrett et al. 2014) and site-specific modelling relating grass biomass to satellite data using time series sensor based data NDVI (Normalized

Difference Vegetation Index) from the Moderate Resolution Imaging Spectroradiometer (MODIS), flown on two NASA spacecrafts (Ali et al. 2014). The main goal of this system is to use Pasture Base ground-truthing and the new Sentinel 2 satellite data from ESA in conjunction with Landsat 8 data from NASA[2], within a machine learning environment, to give weekly estimates of current biomass and total annual grass production at local farm and national levels. These satellite sources along with the active radar satellite Sentinel 1 will also be used to characterize management (grazing, silage, and hay harvesting) at a parcel scale.

Downscaling of Meteorological Data

The most important time-varying agronomic driver of grass growth is weather. The Irish Meteorological service (Met Éireann) collects daily data at climatological, synoptic and rainfall stations. Operationally this data is then assimilated into the Harmonie Numerical Weather Prediction (NWP) model (Seity et al. 2011; Van der Plas et al. 2012) developed by HIRLAM[3] consortium .

Harmonie is run at 2.5 km resolution four times daily, assimilating ground and remote observations. In addition, Met Éireann is currently completing a re-analysis of Irish weather data for the period from 1980–2014. Re-analyses are model "forecasts" that assimilate all the available observations over the period, thus producing a consistent gridded historical weather dataset. In order to understand the drivers of grass growth, the weather and soil parameters from the NWP model will be compared to the remote sensing based grass growth measures.

Understanding the Agronomic Drivers of Grass Growth

The current *Pasturebase Ireland* analysis (Griffith et al. 2014), based on farmer collected grass management data in Ireland, suggests that pasture performance (growth rate, accumulation, growing season, etc.) variation is much wider over smaller scales than existing models suggest. Current agronomic studies include fixed effects of environment implicitly rather than explicitly, and analyze climate rather than weather. This allows for the coarse capture of general agronomic performance as a function of location but does not allow for a detailed understanding of the interaction of management, environment and weather in farm performance. By explicitly building a spatial and temporal model of environmental and weather impacts will enable better understanding of issues such as risk (e.g. how exposed are farm systems to bad weather) and agronomic potential.

The next stage in the analysis is to understand the spatial drivers of grass growth. The dependent variable is based on the grass growth data measured using remote sensing. Based on earlier work from a single site (Hurtado-Uria et al. 2013) this study analyzes grass growth across on a varying spatial and temporal continuum. Inputs to the model include:

- Spatially varying soils data from the new Irish Soil Information System (Creamer et al. 2014).
- Spatially varying slope and altitude data.

[2] National Aeronautics and Space Administration
[3] The international research programme HIRLAM (High Resolution Limited Area Model) is a research cooperation of European meteorological institutes. The aim of the HIRLAM programme is to develop and maintain a numerical short-range weather forecasting system for operational use by the participating meteorological institutes.

- Time and spatially varying weather data.
- Spatially varying farm management data (livestock density) taken from the Census of Agriculture and potentially extended to time and spatially varying livestock density data taken from Administrative Data.
- Farm systems data from spatially enabled NFS.
- The model will combine dependent and explanatory variables using a spatial panel data statistical model to understand the relationship. Panel data analysis, with time-series satellite data treated as cross-sectional data at the pixel level, is the analytical bridge between remote sensing and agronomy approaches. Spatial (Baylis et al. 2011) and Geographical Weighted Panel data (Cai et al. 2012) approaches will also be of particular importance. Methods will be expanded from the area based, neighborhood (spatial lag) analysis approaches encountered in the literature to work with the available point and continuous surface data. The use of spatial panel data is a new and still developing analytical area and its combination with remote sensing data provides a novel approach which will make a significant contribution to the existing literature.
- One of the challenges of using some of these data sources is that the variables are not necessarily collected at the same spatial scale. For example, both the Soil Information System and the meteorological data are modelled, but spatially mapped surfaces are at different resolutions. This may have implications for determining the spatial resolutions that are most appropriate for the analysis. The explanatory power of the model will be tested at different spatial resolutions and develop estimates of the confidence intervals for this geo-statistical model at these spatial resolutions.
- Through the application of the Spatial Panel Data Analysis and Geographically Weighted Panel Regression methods, our ultimate aim is to develop a spatial agri-econometric model linking biomass accumulation to biomass utilization and to test scale dependency in the model. The model framework will develop.
- Develop a spatial model which includes environmental and management factors that explain temporal and seasonal variation in pasture growth performance in Ireland.
- a high-resolution map of pasture performance zonation in Ireland – identifying areas of potential under-performance as a result of prevalent environmental conditions.

Incorporating Real-Time Data Changes to Model Grass Growth: Data Assimilation

The availability of real-time data for meteorological components and for grass growth allows for real-time validation and improvement of the models using the data assimilation techniques used in meteorological forecasting. We propose to improve the real-time predictive capacity of farm specific annual grass and net grass supply models using data assimilation in the land and grass models.

Harmonie contains a land surface model, the SURFEX model (Le Moigne et al. 2009). This provides temperature, evapotranspiration and surface roughness parameters to the atmosphere component. Hence, this model contains a live model of the soil temperature and moisture characteristics of Ireland; to date, this information has not been evaluated. It is planned to progressively implement an ensemble-based data assimilation into a coupled land model, adding in-situ and remote observations of soil and vegetation to the model(s) and generating an ensemble of weather outcomes, which can be used to investigate variability in the grass growth model at the farm level.

An ensemble of initial states for Harmonie based on soil moisture, temperature, and agronomic characteristics will be tested to determine the effect on variability, and compared to observations. During the ensemble modes, the model runs with slightly different initial conditions are used to capture the variability and predictive skill of the forecast (Iversen et al. 2011).

The SURFEX surface model uses the ISBA soil model to provide soil temperature and moisture. This describes soil in terms of simple sand and clay fractions and soil depth. In addition, tree height and Leaf Area Index (LAI) are provided.

Currently, land observations are not assimilated by the Irish meteorological service; the soil state is driven by meteorological fluxes at the surface only. Assimilation will be enabled and tested based on observations from SMOS (Mahouf and Balsalmo 2015), ASCAT (Barbu, 2014); and Sentinel-3 (Lewis et al. 2012). Soil temperature and moisture at selected stations will be used to validate the soil state.

The Soil map of Ireland (Simó et al. 2014) provides detailed information on the soil composition. This will be used in the initial ensemble vectors. Similarly, the vegetation state in SURFEX is currently based on historical averages from ECOCLIMAPII (Seity 2011). This can instead be updated directly from the grass model and remote observations.

SURFEX currently has two assimilation methods, Optimal Interpolation (OI) and Extended Kalman Filter (EKF) (Duerinckx et al. 2012). Modern developments are typically based on Ensemble methods such as Ensemble Kalman Filtering (EnKF) (Evensen 2003). Such methods are preferable as coupled models become more complex (such as where grass models are driven by weather models). Here, EnKF or Bayesian Model Averaging may be applied. BMA has been used with Harmonie within the GlamEPS project (Iversen et al. 2011) which included Met Éireann and ICHEC and for high-resolution wind forecasting (Peters et al. 2013). EnKF is also suitable for land data assimilation (Zhou et al. 2006).

Linking Bio-physical Processes and Farm Data using Microsimulation and Farm System Bio-Economic Modelling

Microsimulation Modelling of Base Dataset

In order to understand the impact of differential agronomic conditions and grass growth across the country, it is necessary to link this data to farm systems, farm size, and animal demographics. In a subsequent step, this information will be linked to farm management decisions and outcomes, which will then be linked to market prices to model the consequential market impact of the interaction between these bio-physical processes.

In a fully operational decision support tool, we would utilize actual farm data (taken from administrative registers) along with spatial data and remote sensing, to provide simulated benchmark data for specific farms. However, there remain a number of challenges to achieving this in relation to accessibility and data cleaning. Therefore, we use synthetically generated representative data using data enhancement methods to create a synthetic spatial farm dataset (see O'Donoghue et al. 2013).

Because we require individual financial data, we cannot use small area analysis for this purpose (Ghosh and Rao 1994). Therefore, we require a method that maintains both spatial variability and micro-level variability such as spatial microsimulation (Clarke 1996). There is extensive literature described in O'Donoghue et al. (2014) covering many different policy areas, utilizing methodologies described in Hermes and Poulsen (2012).

In determining the methodology to use for the creation of a farm level spatial microsimulation model, we face a number of issues. While Iterative Proportional Fitting (Deming and Stephen 1940) could potentially be used to produce small area weights, it struggles to deal with the issue of heterogeneous stocking rates. Similarly, given how many districts have small numbers of farms in Ireland, the Deterministic Reweighting method (see Tanton et al. 2011) is potentially challenging. Simulated Annealing (Williamson et al. 1998; Ballas and Clarke 2000) was used to generate an earlier version of the model (Hynes et al. 2009) but has significant computational costs and also struggles with the spatially heterogeneous stocking rates.

Thus, we will use a methodology that is sample-based in order to (a) avoid the income smoothing concern of the weighting methodology; (b) be computationally efficient, and; (c) adjusted to improve the spatial heterogeneity of stocking rates. We utilize a method developed by Farrell et al. (2013) known as Quota Sampling (QS) which is a probabilistic reweighting methodology, whereby survey data are reweighted according to key constraining totals for each small area.

In this analysis, the farm-level survey data (NFS) is statistically combined with spatial Census of Agriculture data. The most recent Census of Agriculture was collected in 2010 and combined this with the Teagasc National Farm Survey (Hanrahan et al. 2014).

Bio-Economic Systems Modelling

Once estimates of bio-physical drivers of income are modelled at point scale, we will then need to understand how this affects the on-farm profitability at those points. For this, a bio-economic modelling system is required that links these characteristics to financial outcomes across a range of farms within their spatial agronomic context. Bio-economic systems models facilitate the integration and synthesis of knowledge from many areas of research including animal growth, grass growth, feed utilisation and farm management. In the context of the present study, the bio-economic systems model combines fluctuations in grass availability, farm-level characteristics such as animal demographics and ensuing stocking rates, which are the principal drivers (together with input and output price volatility estimates) with which to generate farm profit fluctuations.

Thus, at the core of the modelling system will be a bio-economic farm systems model that models the biological processes on farms of a particular type, with agronomic and grass growth conditions taken from the spatial weather and grass growth models and relates financial outcomes to biological processes across a range of heterogeneous farms.

At present, the models of this type used by the authors are single farm models and are based either on experimental farm data or utilise the characteristics of "average" survey farms (Crosson et al. 2006). Most farm systems models utilize typical farm data based upon experimental conditions (Doole and Romera 2013; Doole et al. 2013; Chardon et al. 2012). These models have been used to simulate the impact of changes in farm practices and technological adoption.

A significant agricultural systems research literature exists which analyses the components and relationships of the whole farm system to elucidate performance outcomes associated with both “endogenous” and “exogenous” activities to the system (Gordon 1969). A range of descriptions and applications of systems models have been published, many of which can be classified as mathematical programming models of production (Janssen and van Ittersum 2007).

Most models are based on hypothetical or representative farm types (Crosson et al. 2006; Wallace and Moss 2002) and have been typically developed for specific applications or locations. Whilst there are notable examples (such as Rotz et al. (2005) whose model includes weather and soil effect), few models have been developed to address multiple assessment areas or geographic locations, i.e. employ a generic framework or are designed to enable upscale of results to higher systems level such as national scale. Examples of models which have employed such generic frameworks to model farming systems for a variety of research questions include the German MODAM model (Kächele and Dabbert 2002; Zander 2001), the Australian MIDAS model (Pannell 1999), the European FSSIM model (Louhichi et al. 2010a, 2010b), and the Scottish ScotFarm Model (Shrestha et al. 2014). However these models are typically designed to model representative farm types based on a specific typology defined by some combination set of farm size, production intensity, production system (dairy, sheep, beef, etc.), biophysical descriptors, etc., in order to analyse grouped farms with similar characteristics in specific regional or agronomic zones.

There is thus a scientific gap in being able to model the impact of management and technological characteristics across a range of actual farms. In Ireland, Shrestha et al. (2014) developed a relatively simple bio-economic systems model utilizing typical farms on a regional basis with a simpler production system than the Moorepark Dairy Systems Model. A similar methodology has been employed in Scotland by SRUC (Barnes et al. 2014). At a European scale the European-wide equivalent dataset to the Teagasc National Farm Survey, the Farm Accountancy Data Network has been employed to develop systems models at a disaggregated scale (Janssen et al. 2010; Louhichi et al. 2010a, 2010b; Van Ittersum et al. 2009) using geo-referenced data (Green and O’Donoghue 2013).

However, both types of models could be criticised for having less realistic bio-economic systems than the single farm systems model. In particular, they lack the capacity to relate farm level outcomes to localised environmental and weather conditions and do not incorporate grass supply, which is one of the primary determinants of purchased feed for animal-based systems.

Simulation

To develop the base dataset of farm characteristics on which simulation will be based, we will utilize spatial microsimulation techniques as follows:

- The quota sampling generates the spatial distribution of farm size, farm system, and soil type, but does not incorporate localised agronomic characteristics such as weather, altitude.
- In order to make these data consistent with agronomic and grass growth data, we will estimate statistical models of the animal demographic, output and cost dependent variables in the Teagasc National Farm Survey as a function of farm and spatial characteristics (geo-referenced cost and production functions). This utilizes

geo-referencing of NFS linked to agronomic and environmental characteristics at the location of the farms.

- Utilizing the estimated statistical models, we can adjust the dependent variables using microsimulation to account for the localised agronomic characteristics. While localised ex-post calibration has been undertaken in the literature using alignment or calibration (Li and O'Donoghue 2014), agronomic based ex-post adjustment has not yet been used in the literature due to the unavailability of suitably geo-referenced micro data. The methodology developed here will extend the literature enabling these models to be used for more spatially disaggregated analyses such as the interaction between farming and water quality.
- In order to be able to create a localized farm financial information system, we will eventually develop a heterogeneous farm system model for dairy, cattle and sheep. However, the framework will initially be piloted for simpler sheep systems. This model will take as input the agronomic, grass growth, system, and animal demographic characteristics of the farm. Specific model components will be generated including the following modules: Animal type specific nutrition requirements; Feed Demand; Other Inputs; Farm Output; Market price and profit module linking volume inputs and outputs to prices utilizing methodology used in Shalloo et al. (2004) and Crosson et al. (2006), however applied to heterogeneous data. For annual income profit analyses, price projections from Teagasc Agricultural Outlook modelling will be used. Subsidies will be treated exogenously, given decoupling of CAP payments.

We allow for differential farmer engagement so farmers could access (top, middle and bottom) benchmark information for a farm with their agronomic characteristics, size, stocking rate, and system). Other farmers who interact with systems such as the eProfit Monitor could avail of greater detail as to their relative efficiency. To do this, we will simulate various versions of the model with different levels of actual and simulated data and compare it against raw data. As the simulation process and system are stochastic, we will use Monte Carlo simulations with different random numbers to develop confidence intervals for different farms.

Data

In a fully operational decision support tool, we would utilize actual farm data taken from administrative registers, spatial data, and remote sensing to provide simulated benchmark data for specific farms. However due to accessibility and data cleaning issues, we need to utilize an alternative data source in order to develop the FARMFIS model.

The CSO Census of Agriculture contains the spatial distribution of farms by the system, farm size, animal numbers, etc. In many ways, it contains similar data to that available on administrative registers. Similarly, detailed farm level data is available through the Teagasc National Farm Survey (NFS). Although these data have recently been geo-referenced and can be linked to spatial agronomic conditions, with a sample of about 1000 farms, the sample size is not sufficiently large to be able to undertake spatially representative analyses.
Therefore, as in the case of other spatially specific analyses, we will use synthetically generated representative data using data enhancement methods to create a synthetic spatial farm dataset, combining the best of both farm-level survey data and spatially disaggregated Census of Agriculture data (See O'Donoghue et al. 2013).

Scoping the Use of Administrative Data

In order to operationalize the Farm Financial Information System, we utilise existing administrative data sources and large complementary remote sensing spatial data assets. Examples of existing data include:

- Animal movement data are recorded on the Department of Agriculture Food and the Marine (DAFM) Animal Movement and Identification System (AIMS) system;
- Land use and land area on the Land Parcel Information (LPIS) system;
- Farm characteristics in the CSO Census of Agriculture;
- Farm subsidies on various DAFM administrative registers;
- Soils data in the Teagasc Soil Information System and the Soil Sample database;
- Agronomic and environmental data on Teagasc and EPA Spatial databases;
- Meteorological data from the Irish Meteorological Service ground stations; grass growth through satellite-based remote sensing;
- Fertiliser use in the Teagasc Nutrient Management Planning Software;
- Detailed farm activity data in the Teagasc National Farm Survey Database; and
- Farm financial data on the Teagasc eProfit Monitor system.

It is evident that much of the data needed to develop a predictive information system that can provide this benchmark system already exists. However, the back-end statistical, spatial analysis, agricultural systems, behavioral and ICT science needs further work to develop the capacity to process this data. Importantly, an appreciation of the potential use of integrating big data sources does not yet exist.

Summary and Next Steps

In this paper the development of a blueprint is described for a modelling framework to develop a Farm Financial Information System (FARMFIS) to assist farmer financial decision making, which will builds upon existing big data resulting from administrative, remote sensing, meteorological and survey data and a variety of different model methodologies to produce localized farm information.

Farmers who utilize FARMFIS could improve their financial and environmental performance by:

– improving their cost management through benchmarking against technically more efficient peers;

– making decisions about appropriate animal stocking rates that can improve both financial and environmental performance;

– adopting appropriate farm systems (dairy, cattle, sheep, tillage) appropriate to their capacity, land and financial needs;

– improving nutrient management; and

– making better investment decisions.

Real-time and predictive information about feed requirements and availability over the course of the year at a localized level would assist extension advisors to provide targeted local advice to provide early warning systems during difficult times. For example, national media coverage of the Fodder Crisis in 2013 gave the impression that the impact was nationwide, whereas in reality according to Teagasc remote sense information, the impact was more localized. Additionally, this information would allow for a prioritization of resources on a spatial basis. It would also improve the capacity of advisors to provide localized agronomic and planning advice to farmers.

Improved localized agronomic financial information can allow for:

- improved estimates of Soil Moisture by the Irish meteorological service;
- a better understanding of the impact of improved financial management by policy makers within the Department of Agriculture Food and the Marine; and
- assisting in the dissemination of key financial planning messages across a range of financial, agri-business and training stakeholder partners in the Getting Farm Financially Fit agri-sector network.

This paper provides a framework to make it easier to provide predictive financial information, drawing on a wide variety of big data sources and current financial and economic modelling techniques in the agricultural setting. However, modelling capability and data are not sufficient for the system to have an impact on facilitating decision making by farmers. The process by which farmers engage with financial data and make financial-related decisions is highly complex and crucially involves mediating farmer behavior (Macken-Walsh et al. 2015).

The experience of the agricultural extension experts in the project team is critical to maximizing impact as they provide an understanding of how farmers engage with this information and how they make consequential decisions. The prototype described in this paper forms the back-end analytical solution. In order to fully engage farmers, it requires co-designing with farmers on the front-end and interpreting the predictive financial data in a way that is meaningful to farmers.

In order to maximize the effectiveness of the approach, it will be necessary to provide outputs from the decision support tool in ways that are accessible to farmers with different technical skills. These will vary from online interactive tools for farmers with the need to access more detailed information, to simpler dissemination tools utilizing smart phones and support materials, as well as more general dissemination through farm media.

The contribution of this paper to the literature and novelty of the approach lies in the fact that while big data has been used extensively in precision agriculture in terms of agronomic decisions, real-time decision tools that focus on predictive full-farm financial benchmarking, utilizing real-time administrative and satellite data are new. The paper describes the conceptual blueprint that is being utilized by a team of Ph.D. students, agricultural extension specialists, agricultural economists and spatial analysts in developing a functional back-end system. Given the complexity of the modelling framework used as part of the decision support tool, the purpose of this paper is to outline the methodology in advance of the operational implementation of the framework.

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