Spatial Analysis of Viable Farms

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Abstract

An economically viable farm is defined as having the capacity to remunerate family labour at the average agricultural wage, together with a return of 5 per cent on non-land assets. There is however significant spatial heterogeneity among farms. In this paper we examine farm viability using a classification concept (Frawley and Commins, 1996). A spatial microsimulation approach is used to add a spatial component to a farm micro dataset. This dataset is then linked to a spatial micro dataset of households which allows for farm and non-farm analyses within the same analysis. This dataset enables us to analyse the characteristics of the areas within which viable farms exist in addition to the farms themselves.

Introduction

In this paper we examine the spatial distribution of farm viability. Two separate spatial microsimulation models are developed; one for farms and one for households. The former links the National Farm Survey (micro data) to the Census of Agriculture and the latter links micro household income data (the Living in Ireland Survey) with the Census of Population. A statistical matching algorithm that generates a micro dataset with the characteristics of the spatial control dataset is utilised in our model (Farrell et al., 2010). Our model also contains additional data on indicators of sustainability as well as spatial amenities of an area.

Hennessy (2004) and Frawley and Commins (1996), define a useful classificatory concept known as viability where an economically viable farm is defined as having the capacity to remunerate family labour at the average agricultural wage, together with a return of 5 per cent on non-land assets. A farm is considered sustainable if they are not viable, but have off-farm employment. The residual category is neither viable nor have off-farm employment and is thus unlikely to be sustainable in the long term. We term this category vulnerable. This classification allows farm's incomes to be grouped into one of three categories.

There is significant spatial heterogeneity in Ireland (Crowley et al., 2008), with by and large the better land in the South and East and the poorer land in the North and West (Frawley and Commins, 1996). The most profitable sub-sectors within agriculture tend to be dairy and to some extent tillage farming which are predominantly concentrated in the South and East. The lower margin beef and sheep sectors are to a large extent located in the Midlands, North and West of the country. However in addition to the spatial heterogeneity in farm income sources, there is also significant heterogeneity in employment, types of employment and access to labour markets. The drystock sector (sheep and beef) tend to be more likely to have off-farm employment, whilst access to employment is likely to be higher in the south and east. It is important to understand this spatial heterogeneity to pattern target policy interventions.

Sustainable agriculture is defined as a practise that meets current and long-term needs for food, fibre, and other related needs of society while maximizing net benefits through the conservation of resources to maintain other ecosystem services and functions, and long-term human development. It emphasizes the multidimensional (economic, environmental and social) goals of sustainable development in agricultural terms (Rao and Rogers, 2006). The concepts of economic and social sustainability essentially underpinned the creation of the Common Agricultural Policy (CAP) in the 1960s through its objectives of sustaining an adequate standard of living and a secure food supply. While this focus continues to this day, the objectives have broadened to include a broader territorial or spatial based rural development objective as well as environmental based objectives.

Indicators of sustainability assist policy makers in targeting resources and policy at particular dimensions. They help to improve transparency, accountability and ensure the success of monitoring, control and evaluation of sustainable agriculture measures (Matthews, 2003). Whilst a previous study, Dillon et al. (2010) developed indicators in relation to the national population of farms, the shifting policy context requires the development of spatial based indicators. Indicators of sustainability seek to describe and measure key relationships between economic, social and environmental factors with sustainable development being seen as a better balance between all three dimensions (FAO, 2003:4).

The ability to characterise and summarise areas in which farms are largely viable or not viable has enormous benefits to better inform agricultural policy. Perhaps it can lead to spatial explanations as to why some areas are performing better than others.

Policy Context

Efforts to increase productivity in Agriculture go back centuries to the Agricultural Revolution and was an important focus of development policy in Ireland since Independence (Kennedy et al., 68) and although stagnant until after the second world war, a number of government programs saw agricultural output treble between 1950 and 1972 (ibid: 69). Output increased by 20% between joining the EEC in 1972 and 1984 (ibid: 83).

The concepts of economic and social sustainability essentially underpinned the creation of the Common Agricultural Policy (CAP) in the 1960s through its objectives of sustaining an adequate standard of living and a secure food supply. While this focus continues to this day, the objectives have broadened to include a broader territorial or spatial based rural development objective as well as environmental based objectives.

As has been mentioned the Common Agriculture Policy (CAP) has seen a continuous trend in moving away from a primary focus on supporting agricultural production to have increased support for restructuring and diversification. The MacSharry reforms in the 1990's saw a movement away from predominantly relying on price supports to coupled income supports related to production. The Agenda 2000 reform of the CAP signalled a major change in the philosophy of European agricultural policy by introducing the concept of a second pillar, i.e., not just supporting agricultural production (the first pillar) but supporting the provision of environmental and social services and encouraging diversification of activities both on and off-farm. The Luxembourg Agreement in 2003 saw the decoupling of income supports to be unrelated to production and strengthened the rural development pillar of the CAP under which farmers receive additional payments where they are farming in less favoured areas or are enrolled in an agri-environment scheme.

Within the policy context, this basic instrument of the CAP aimed at supporting prices of agricultural commodities remained unchanged for its first 30 years (1962-1992) with environmental sustainability first appearing in the McSharry reforms in 1992, introducing a set-aside scheme in the arable sector and contained three accompanying measures, including an early retirement scheme, an agri-environment scheme and a scheme for afforestation.

Later, the European Council in Helsinki (December 1999) adopted the Strategy for integrating the environmental dimension into the CAP.

The Agenda 2000 reform of the CAP signalled a major change in the philosophy of European agricultural policy by introducing the concept of a second pillar, i.e., not just supporting agricultural production (the first pillar) but supporting the provision of environmental and social services and the promotion of quality products. The Mid-Term Review (MTR) in 2003 or The Luxembourg Agreement strengthened the rural development pillar of the CAP under which farmers receive additional payments where they are farming in less favoured areas or are enrolled in an agri-environment scheme which prevents pollution and protects habitats, which recognise the public goods (bio-diversity, landscape) which farming produces. Following Agenda 2000, environmental and rural development measures were brought together into a single Rural Development Regulation. The European Council in Göteborg (June 2001) endorsed the European Union strategy for sustainable development, adding the environmental dimension to the social and economic ones. Other relevant policy instruments include the Bird and Habitat Directives and the Water Framework Directive.

Within the CAP, the Less Favoured Areas support payment is made to farms in areas affected by specific handicaps. Across the EU about 57% of agricultural land is covered by the scheme (CEC, 2009). The European Court of Auditors in 2003 have called for a review of the classification of areas of intermediate handicap with changes to be implemented from 2010 (ibid.). However data based limits in relation to the spatial impact of this policy has limited the capacity to change the policy. CEC (2009) have suggested a number of spatial biophysical attributes that should be used in developing a new policy.

Thus over time has been a gradual change within the CAP from a sectoral focus to a territorial approach. In this new rural paradigm (OECD, 2006) where rural development focuses less on specific sectoral characteristics such as agriculture and more at a multi-sectoral approach aimed at increasing welfare through multi-dimensional instruments. These vary from broader economic development recognising the role of non-agricultural employment in supplanting agriculture as the economic driver of rural areas to differential public policy specifically focusing on delivering programmes such as health policy to areas with low population density.

The European Commission is over the course of 2010 undertaking a consultation exercise to reform the CAP post 2013. While there are as yet no specific proposals as of yet, commentators such as Bureau and Mahé (2008) have proposed a number of changes such as a move from direct payments based upon historical production to a territorial approach where payments will be made on a location specific basis known as a Basic Husbandry Payment. They also propose a Natural Handicap Payment which would promote the continuation of farming in areas with natural handicaps. The third dimension payment, a Green Points Payment (GPP) would promote the delivery of environmental public goods in designated rural areas of high nature value or which are environmentally sensitive.

Thus, reforms of the CAP have increasingly been more aimed at fostering the spatial, environmental and social sustainability of European farming rather than the predominantly economic sustainability focus of the first four decades of the CAP. This reform direction is placing greater demands upon analytical capacities that incorporate a spatial dimension. Spatial data and analytical tools will therefore be the key to understanding and re-designing the focus of policies such as these.

Methodology

As identified above agricultural policy in Europe and in Ireland is increasingly taking a territorial dimension, with an increasing focus on place. Given the very heterogeneous characteristics of different locations due to different environmental conditions, access to markets and population distribution, it is important therefore to have spatial data to inform policy debate and discussions. Secondly within these spatially heterogeneous areas, there is a significant degree of heterogeneity across different farms. Any policy analysis such as the creation of sustainability indicators needs to take this variability into account.

Given the focus on agricultural activity, the environment, social structures and welfare enhancing policies underpinning rural sustainability, to develop sustainability indicators suitable for the analysis of agricultural and rural development policies, we therefore require spatial micro data with the following attributes:

- The distribution of agricultural activity and its economic impact
- The relative contribution of farming and non-farming incomes within farm households and across other households
- The environmental characteristics of agricultural activity (nitrogen use)
- The distribution of demographic characteristics

In this paper two separate spatial microsimulation models are developed; one for farms and one for households. The former links the National Farm Survey (micro data) to the Census of Agriculture and the latter links micro household income data (the Living in Ireland Survey) with the Census of Population. A statistical matching algorithm that generates a micro dataset with the characteristics of the spatial control dataset is utilised in our model (Farrell, O'Donoghue and Morrissey, 2011).

Each of the three sustainability indicator categories are examined, environmental, economic and social. In the environmental case we focus on nitrogen levels and usage. This will incorporate the spatial elements of soil type and weather. You would expect areas with poorer soil quality to use more nitrogen on their land. In the economic case we look at whether a farm is viable or not. This will be impacted by access to markets, local labour markets as well as farm size. And lastly we look at the social indicator of rural isolation. That is whether or not a farmer lives alone. Population density, demographics of the area will be impacting here.

While the household model has aggregate farm income, it does not contain detailed farm level income required for more in depth analysis. For this we need to match the two spatial datasets. This step requires statistical matching. Due to the relatively few overlapping variables between the two datasets, we utilise a Grade Correspondence method a commonly used technique, where farms are matched on the rank of income (Decoster et al., 2009).

Data

The data we require in relation to farms comes from the National Farm Survey (NFS). contains detail farm enterprise level micro data on farm activities (See Connolly et al, 2009). However this data is only available at the national level and only spatially representative to the NUTS3 level. A range of household surveys including the Household Budget Survey (HBS), the Living in Ireland Survey (LII) and the Survey of Income and Living Conditions (SILC) contain the distribution of incomes, labour market and demographic characteristics, but again are only representative at the national level and with limited agricultural data. The Census of Population Small Area Statistics contain spatially disaggregated data (3400 districts) on economic activity and demographic characteristics, but is not available at the micro level and does not contain incomes. Similarly the Census of Agriculture is available at this spatially disaggregated level, but again has the same flaws as the Census of Population. There are good spatial environmental characteristics available in the Teagasc spatial data archive, however this GIS based data is not linked to activity. Therefore, unfortunately no single dataset provides such a range of data, either at the national level or particularly at the spatial level.

Spatial microsimulation which is a methodology designed link using statistical methods data to produce data that can be used to analyse the spatial implications of economic development and policy changes (Holm et al., 1996), seems ideal for this purpose. A microsimulation model uses microdata on individuals, farms, firms, etc. to build large-scale data sets based on the real-life attributes of individuals, farms or firms and then simulates the effect of changes in policy on each of these units. By permitting analysis at the individual level, spatial microsimulation methods allow one to assess both between location variation and within location variation across farms and households (Ballas et al., 2005 and Holm et al., 1996). These models are flexible in terms of spatial scale in that they can be re-aggregated or disaggregated. For example, the model developed in this paper can be aggregated to counties (by ED) or regions (by province). Third, spatial microsimulation models store data efficiently as lists; the lists generally consisting of unidentifiable units with associated characteristics obtained as mentioned above, from a survey or census.

Model Construction

In order to create a spatially microsimulated dataset for use in the development of sustainability indicators, we need to undertake the following steps:

- Create a spatial micro dataset of farms, containing the spatial distribution of agricultural activity and incomes
- Create a spatial micro dataset of households, containing the spatial distribution of other economic activity and incomes, consistent with spatial demographic characteristics
- Link the two spatial datasets via statistical matching to allow for farm and non-farm analyses in the same analysis
- Link the generated spatial micro dataset to GIS layers of environmental attributes and rural services.
- Simulate agricultural outputs that may impact upon the environment such as Nitrogen compound production and Methane production.

Spatial Distribution of Rural Households and Farm Enterprises

Fundamental to the creation of a spatial micro dataset using microsimulation techniques is a statistical matching algorithm that generates a micro dataset with the characteristics of the spatial control dataset. Our objective is to undertake analyses based upon the spatial distribution of both agricultural income and activity and of wider household incomes. As no single set of data (either at micro or spatial scale) contains detailed farm and household information, we develop two separate models; one for farms and one for households. The former links the National Farm Survey to the Census of Agriculture and the latter links micro household income data (the Living in Ireland Survey) with the Census of Population.

A number of methods exist to undertake the statistical matching exercise. These include iterative proportional fitting, simulated annealing, deterministic reweighting, generalised regression reweighting and quota sampling (See O'Donoghue et al., forthcoming a) for a description of these methods.

Various stages of the model development have used different methods. The first variant focusing on population demographic issues (Ballas et al., 2006) used iterative proportional fitting to generate the model. Hynes et al. (2009b) developed a farm level model using simulated annealing, while Morrissey et al. (2010) developed a household level model for rural service provision analysis, again using simulated annealing. While simulated annealing is reasonably accurate, it imposes significant computational constraints due to the length of time required to undertake the match. Farrell and O'Donoghue, (2010) have developed a method based upon simulated annealing that samples data from a micro dataset in accordance with "quotas" provided by spatial control data from the census, using randomised sampling without replacement to improve the computational speed of selection.

Table 1 describes the match variables. These variables meet the requirement of being available in both the sampling datasets (NFS and LII) and in the spatial constraint data (Census of Agriculture and Census of Population respectively). Given the computational cost of adding extra variables, which increases at a non linear rate, we are limited in the number of constraints that can be used. A particular feature of the method used in this paper is that multiple units of analysis can be used, so that individual constraints such as the number of people by education can be combined with a household unit of analysis in the sampled dataset. This allows sub-levels such as individual and family or farm sub-enterprise to remain consistent with the higher level unit such as household or farm. O'Donoghue and Morrissey (forthcoming) have found that the method almost perfectly replicates the control totals described in table 1 and performs satisfactorily when compared against high level external validation totals not used in the creation of the model.

Table I.1. Model's Baseline Variables, Categories and their Dataset Source

	Sample Data	**Census Data**
Farm Level		
Farm Size (6 groups)	NFS	Census Of Agriculture
Farm System (7 groups)	NFS	Census Of Agriculture
Dominant Soil Type (5 classes from wide use range to soils where the agricultural potential is very restricted).	NFS	Soil Map of Ireland
Number of Farms in each ED	-	Census Of Agriculture
Household Level		
Number of People by Age Group and Sex (? Groups)	LII	Census of Population
Number of People by Education Level (? Groups)	LII	Census of Population
Number of Households in each ED	-	Census of Population
Is a Farming Household	LII	Census Of Agriculture

Spatial Distribution of Farming and Non-Farming Income

While this method produces a good match for matching variables and high-level validation comparisons (county poverty rates), we find the assumption of conditional independence required in statistical matching is broken for many non match variables. Essentially this results from the fact that the variables used for the statistical matching do not capture all spatial heterogeneity. In other words the spatial variability of variables such as employment status depends upon other characteristics than the spatial pattern of age-sex-education. Examples may include the spatial pattern of occupation or characteristics associated with local labour markets.

One alternative is to increase the number of constraint variables, to for example include the number of workers within an ED as a constraint. While this is feasible, the computational cost is quite high given the fact that the match needs to take place for 3400 districts. In any case also, the same issue will arise for lower order variables, so that while the proportion of people in-work may be correct after a match, it would be less likely to capture the spatial pattern of having a greater proportion of self-employed within the district. Instead we utilise an alternative method drawing upon our experience in dynamic microsimulation modelling (See O'Donoghue, 2000).

This mechanism is based around model calibration. The objective of calibrating a spatial microsimulation model is to ensure that the simulated output matches exogenous totals at varying levels of spatial disaggregation (Baekgaard, 2002). Similar to the CORSIM (Caldwell, 1996) and DYNACAN (Morrison, 2006) models, SMILE incorporates a system of regressions with the non-matched variables as dependent variables, combined with an array of alignment processes (See O'Donoghue and Morrissey, forthcoming). There are a number of different alignment processes one may use and the choice of process depends on the type of data outputted from the microsimulation model and the data type of the exogenous 'target' data. In our model we utilise three types of alignment for binary discrete data, discrete data with more than two choices and continuous data.

Average county income by income source are calibrated to county level national accounts. Due to definitional differences, which if adjusted for can seriously affect the distributional properties of the data, instead of scaling average income by source to the national accounts total, we adjust instead by the ratio of average income by source to the national average (O'Donoghue and Morrissey, forthcoming). Thus by and large we maintain the same distribution properties of the underlying income data. While these are well known under reporting of particular incomes such as capital income and self-employment income (see Atkinson et al, 1995), income surveys are typically not adjusted to account for these issues.

The typical measure used for welfare analysis is disposable income, defined as market income plus benefits minus taxes. We utilise a tax-benefit routine described in O'Donoghue et al. (2010) to generate measures of disposable income.

Linking Household and Farm Models

With our focus on rural development, we need to undertake an integrated farm enterprise-household analysis. While the household model has aggregate farm income, it does not contain farm level detail required to, for example model environmental outcomes. For this we need to match the two spatial datasets. This is done in two stages. Firstly within the household model, we differentiate between having farm income and where farming is the dominant employment status. This is because of the high prevalence of off-farm employment in Ireland where over 50% of farmers have an off-farm job (See Connolly et al., 2009). Thus many individuals with farm income will have a main employment status that is not farming. To ensure consistency between the models, we use the number of farms generated within the farm microsimulation model as a calibration total for the number of farm households within each district. We utilise the continuous alignment function to produce an estimate of total household farm income. The spatial farm dataset also contains a measure of household farm income.

The last step requires us to link the farm households in the household dataset with a total value of farm income with the farm households in the farm dataset with nearly 2000 technical, input and output variables including total farm income. This step requires statistical matching. There are a number of different possible options in statistically matching this data outlined in Decoster et al., (2009). However due to the relatively few overlapping variables between the two datasets, the parametric and non-parametric regression methods as well as the minimum distance methods are not suitable. Therefore we utilise a Grade Correspondence method which is used quite frequently in the literature, where farms are matched on the rank of income. As the farm numbers in the household dataset have been calibrated to the number in farm dataset, both models thus have the identical number of farms per district. We therefore merge on the rank of farm incomes, replacing the farm incomes from the survey with the farm incomes from the farm survey which are consistent with the underlying farm structure variables. Although not examined here, this matched dataset can be used for example to get the distributive impact in terms of household income of farm subsidies targeted at specific enterprises such as the Beef Suckler Welfare Scheme or environmental instruments such as carbon taxes and water regulations.

We also make use of river catchments data from the WFD to estimate nitrogen use by area. Nitrogen use can be used as a proxy for both soil quality and weather. Using GIS techniques we identify which EDs are situated in a particular river catchment. The data for that river catchment is then assigned to that ED. Where EDs overlap with the river catchment boundary, the ED is assigned to the river catchment which contains the majority of its area.

At the end of this process we are left with a spatial rich dataset which contains farm, individual, environmental, demographic, spatial and economic data at a spatially disaggregated scale, ED level in this case. This data enables us to firstly categorise farms in one of three categories, viable, sustainable and not viable or sustainable. Using these categories we can then identify any particular spatial patterns to the results and whether in fact space can determine whether a farm is viable or not.

Applications

Spatial microsimulation methods have been increasingly adopted to study the spatial impacts of social and economic policies (Ballas et al., 2005, O'Donoghue, forthcoming b). There have been a number of related analyses using the framework. Hynes et al (2009) used the farm spatial microsimulation model for spatial farm income and policy analysis. Hennessy et al. (2007), used the framework to assess the spatial and distributional impact of CAP reform. There have also been a number of environmental analyses using the model. For example, Hynes et al, (2009) used the model for spatial environmental analysis of greenhouse gas emissions and Hynes et al. (2008) looked at habitat conservation and participation in agrienvironmental schemes. Within rural development, Morrissey et al. (2008, 2010) utilised the spatial household model for use in assessing rural health services. Cullinan et al. (2008) used the framework to model the demand for recreation in small scale forests.

Results

After combining spatially disaggregate data on farms, environmental data and census data we can perform analysis on the various sustainability indicators.

Environmental Indicator

Firstly we look at the environmental indicator organic nitrogen per hectare. From the WFD dataset we were able obtain an average value per ED. EDs are divided into deciles weighted by the number of farms in an ED. This makes it easier to compare EDs.

Areas with high levels of nitrogen tend to have higher levels of employment and lower levels of unemployment compared to those with low levels of nitrogen. They also tend to have a lower old age deprivation rate but a higher child deprivation rate, which would suggest the areas with the highest nitrogen usage have a younger population. Areas with high levels of nitrogen have a lower number of farms but a greater number of livestock units per hectare which would suggest they are farming more intensively and using more nitrogen on the farm.

Economic Indicator

To examine the economic indicators farm were classified into one of three categories, viable, sustainable and vulnerable. An economically viable farm is defined as having the capacity to remunerate family labour at the average agricultural wage, together with a return of 5 per cent on non-land assets. A farm is considered sustainable if they are not viable, but have off-farm employment. The residual category (vulnerable) is neither viable nor have off-farm employment and is thus unlikely to be sustainable in the long term. After aggregating the farm income data from the SMILE model we get the percentage of farms per ED in each of the three categories. We divide the three categories into deciles and compare the best performing EDs to the worst performing EDs to hopefully find disparaging differences.

EDs with the highest levels of viable farms tend to have higher employment rates for men however the difference is negligible for women, lower unemployment rates, a much lower population density, a lower old age deprivation rate but higher child deprivation rate, a greater stocking rate and higher nitrogen usage.

When we consider farms that are sustainable, those with the highest levels of sustainable farms have lower employment rates, higher unemployment rates, lower levels of tertiary education, lower population density, a higher old age deprivation rate but lower child deprivation rate, lower stocking rate, higher number of farms but also lower nitrogen usage.

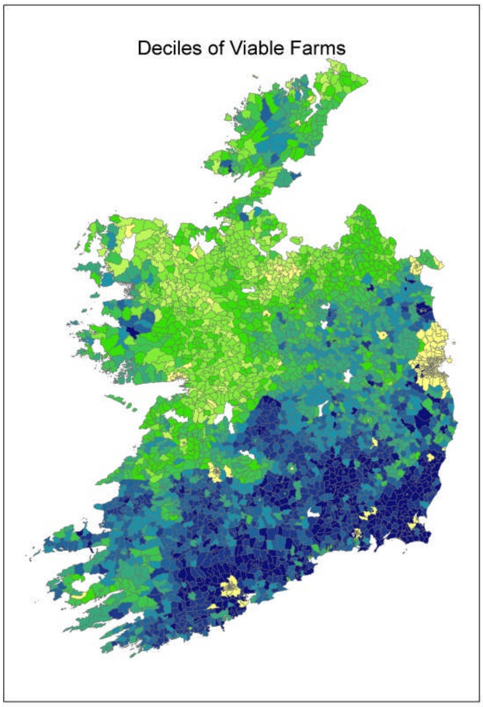
The EDs with the highest levels of vulnerable farms have lower employment rates and higher unemployment rates, lower levels of tertiary education especially for men, lower population density, higher old age deprivation rate but lower child deprivation rate, lower stocking rate but higher number of farms.

Conclusions

In summary it appears that those areas which are the most damaging in terms of nitrogen output appear to be the same areas which are performing strongly economically. They are categorised by high levels of employment and lower levels of unemployment. The higher population density suggests they make be closer to urban areas. They are also better educated and have a younger age profile compared to those areas which are vulnerable. They appear to be farming intensively, the high stocking rate, lower number of farms and higher nitrogen usage would suggest that.

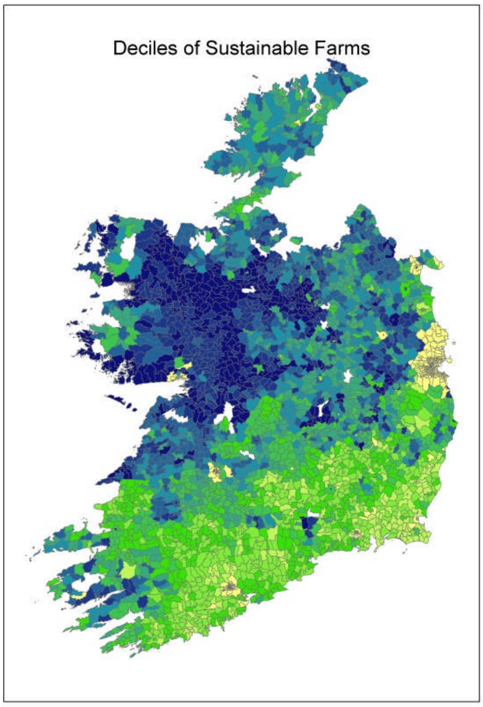
Appendix:

Figure 1: Deciles of Viable Farms



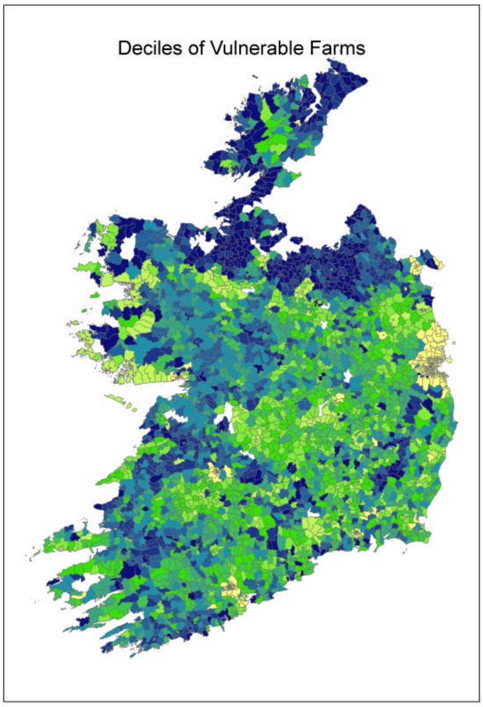
Source: *SMILE*

Figure 2: Deciles of Sustainable Farms



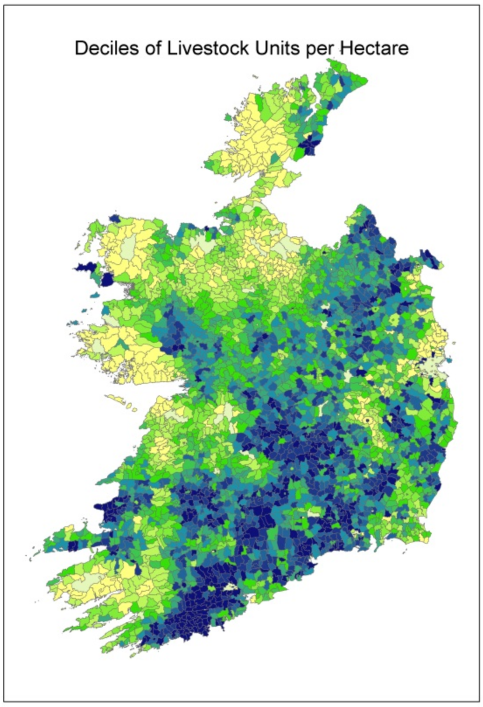
Source: *SMILE*

Figure 3: Deciles of Vulnerable Farms



Source: *SMILE*

Figure 3: Deciles of Livestock Units per Hectare



Source: *SMILE, NFS*

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