REFEREED ARTICLE

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How current environmental and weather conditions affect time critical decision making on Irish dairy farms

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ABSTRACT

In order to understand how current environmental conditions affect farmer decision making the levels of grass and soil condition are examined in the decision on when to turn cattle out from winter housing to spring grazing on Irish dairy farms. Five years of satellite derived Normalised Difference Vegetation Index MODIS data, as a proxy for grass growth data, were used along with daily rainfall data and turn out dates from 199 dairy farms. Using GIS analysis conditions at the time of turn out were determined at the date and location of the event. A panel analysis shows that farmers respond to early growth but not immediately, gaining three and half days extra grazing for every week that grass growth is early. The inertia in decision making around a preferred date was shown by using the previous year's turn out date in the model. We can accurately predict when turn out occurs with a RMSE of 10 days, compared to average on farm range of dates over the 2008-2012 period of 25 days.

KEYWORDS: NDVI; Remote Sensing; Panel Data; Herd Management; Rainfall

1. Introduction

The decision on when to release cattle from winter housing for daytime spring grazing is a critical one on Irish dairy farms which impacts on the length of time a herd are grazing and grazing season length affects farm profits, with research demonstrating that extending the grazing reduces costs (Kinsella *et al*., 2010). In a survey of Irish Dairy farmers in 2008 Creighton *et al*. (2011) found the average grazing season length was 245 days and with respect to turn out dates fodder availability and soil condition were the main factors in the timing of the decision. Field trials have shown that early grazing options across a wide range of stocking densities improve animal and sward performance and are to be recommended in dairy systems (O'Donovan *et al*., 2004). However the situation for specialist beef production in Ireland is not as clear, with work suggesting that the effect on profitability is only marginal and only for some types of beef production system (McGee *et al*., 2014).

In order to understand why farmers do not engage in the management practices that would allow for a longer season, the issues around adoption of extended grazing have been examined by O'Shea *et al*. (2015) within the context of technical adoption theory. Survey results (207 respondents) were analysed as a binary probit model of adoption/non-adoption of extended grazing (defined relative to regional average). Agricultural education and off-farm employment had the most significant positive relationship with participating in extended grazing and past participation in agri-environment schemes had the strongest negative affect on the choice of extended grazing.

An ordinary least squares (OLS) analysis of one year (2009) of the data set presented in this paper, by Läpple *et al*. (2012), found that geographic region and soil status were strongly associated with length of grazing season but that farm size, stocking density or grazing method had no relationship with grazing season length.

Use of satellite data in observing grassland

Here we use daily satellite observations as proxy for grass growth. Remote Sensing, RS, optical satellite systems record reflected sunlight in different wavelength ranges from the earth's surface. The reflected light is determined by the landcover. In the case of vegetated surfaces, the amounts red and near infra-red light recorded in each pixel of the image are strongly related to the amount of biomass at the earth's surface represented by the pixel. Normalised Difference Vegetation Indices, *NDVI*, is the ratio of red and near infra red,

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NIR, light recorded at a pixel.

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

NDVI ranges from zero over area of no vegetation (bare rock, soil, cement *etc.*) up to one for 100% cover of well growing vegetation, like grass in Ireland in May. NDVI is one of dozens of vegetation indices developed over the last 30 years and their use in biomass monitoring is well developed (see Viña *et al*. (2011) for a current overview).In a managed grassland context in Ireland, NDVI has been used to detect spring time phenology events (O'Connor *et al*., 2012), directly estimate grass biomass levels (Ali *et al*., 2016) and predict stocking density (Green *et al*., 2016).

The use of RS derived data in a panel analysis (with or without a spatial component) is increasing as econometrics begins to draw on a new source of independent data that can, though GIS systems, be incorporated into traditional data models.

Aim of paper

In order to understand how current growth and weather influence the timing of major herd management decisions five years of geocoded farm level data recording when animals are first tuned out from winter housing along with contemporaneous satellite derived measures of fodder availability and local rainfall data (as a proxy for soil condition) are analysed. First the environmental conditions present when animals are turned out are characterised and then through a panel analysis those indicators that are most strongly associated with the decision to turn out are discovered.

This model is developed further as a random effects model with time large to predict when a farmer is likely to have turned out given spring conditions. The implications of the model with respect to farmer decision making are discussed.

2. Data sources

Dependent variable: Turn out date

The Teagasc National Farm Survey, NFS, (Hanrahan *et al*., 2014) is collected as part of the EU Farm Accountancy Data Network. It consists of a detailed set of accounts for approximately 900 farms statistically sampling for farm system. Between 2008 and 2012 specialist dairy farmers in the NFS ($\sim$300 farmers each survey) recorded turn out dates. This gave a total of 1536 recorded turn out events (to avoid issues around an unbalanced panel, we chose to use only farms with five complete years of data in the final analysis leaving us with a sample population of 199 farmers). The turn out date is transformed to Julian day of year, with January 1st as 1 etc. So an early turn out date is a low number and a late turn out date a high number.

The farms are linked to environmental variables via location and to achieve this the NFS was recently geocoded (Green and Donoghue, 2013) using address matching methods. To illustrate the geographic distribution, the average (over the five years) turn out date for the farms in this analysis is mapped in 10km tetrads in figure 1. We can see that farms in the south generally turn out earlier than farms in the north.

All recorded turn out dates, 2008-2012, are plotted to look at day of the week when turn out occurs (figure 2a), the day of the month (2b) and day of the year (2c).

There seems to be little bias in day of the week (figure 2a), perhaps a small drop at the weekend, but dairy farmers run a 7 day week operation, so for there to be no day of the week more likely than another when turn out occurs is unsurprising.

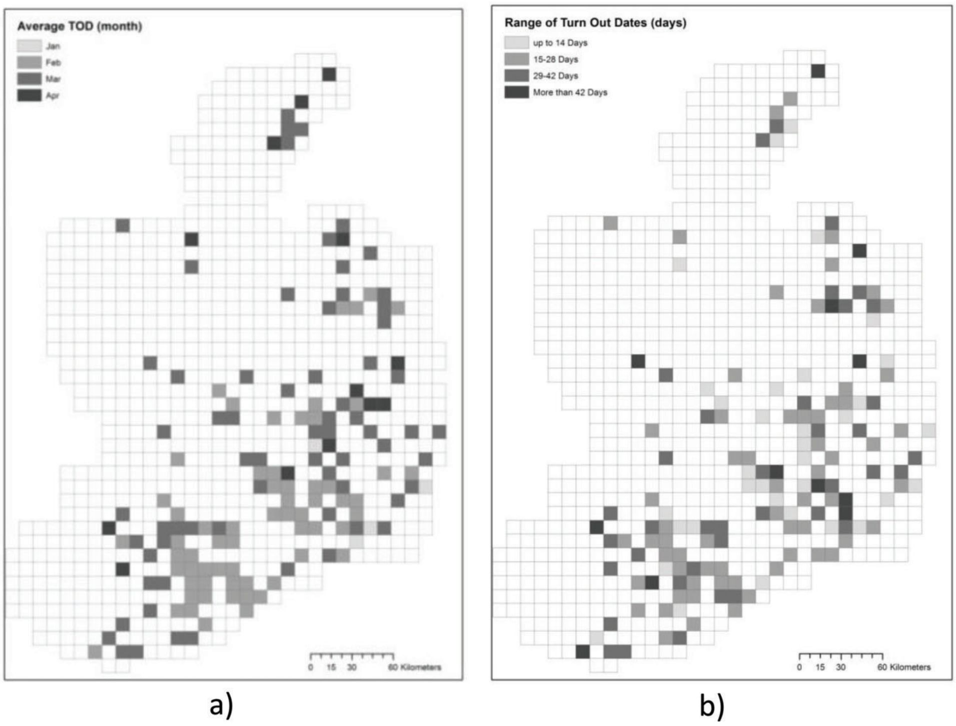

Figure 1: 10km tetrad distribution map of a) average turn out dates (TOD) of the dairy farms in our sample and TOD range over the period 2008-2012

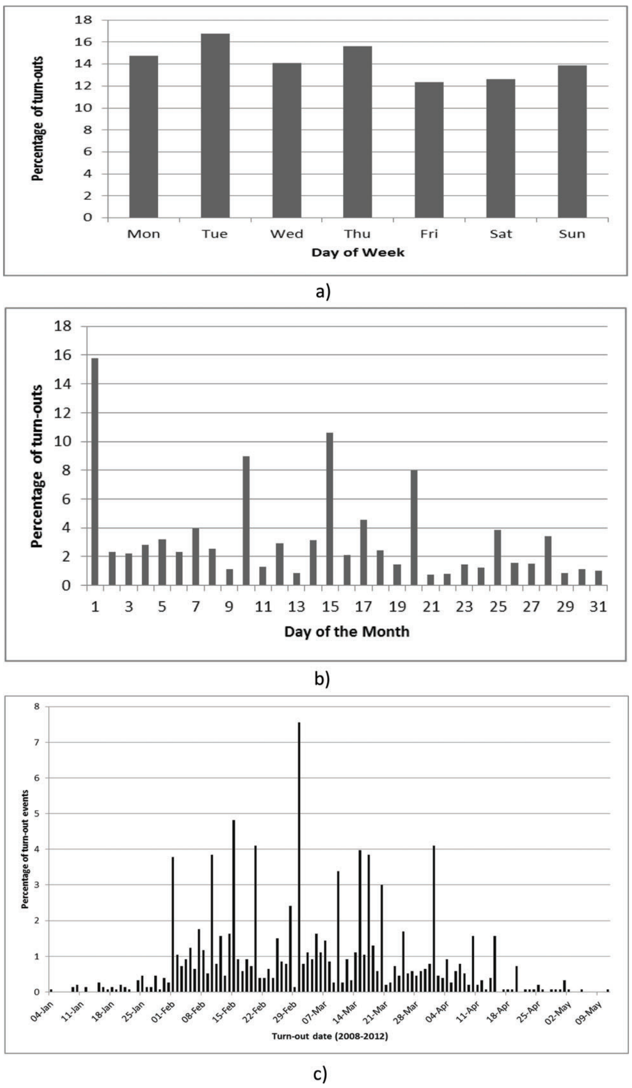

Figure 2: a) day of the week on which turn-out first occurs, b) day of the month on which turn-out first occurs, c) day of the year on which turn-out first occurs, 1536 turn out events, 2008-2012

There is a clear bias toward the 1st of the month when turning out, Figure 2b, this may be farmers responding to advice or defaulting to a habitual day.

Clearly there is no agronomic reason for the start of the month turn out but it must be acknowledged that this decision does not occur in a vacuum and having a fixed date, set in advance, may have personal advantages within a farm household that faces the myriad of competing demands of any other family home.

Figure 2c illustrates that March the 1st is the most favoured turn out day, with February 15th next and then thirdly March 17th, St. Patricks day. It is this apparent tendency for inertia around set calendar days that advice around extending the grazing season seeks to overcome.

Explanatory variables: Satellite observation of grass growth

The satellite data used were 16-day composites of MODIS Normalised Difference Vegetation Index, NDVI, imagery from the MODIS sensor on the Terra satellite (Huete *et al.*, 2002). The selected MOD13Q1 product provided detailed quality flags and Day of Year acquisition stamp for each 250m pixel (García-Mora *et al.*, 2011). Terra satellite records imagery over Ireland every second day, however the majority of these images are contaminated with cloud. In a composite product, the data are examined pixel by pixel across the composite period and the best quality pixel is identified and its value and day of acquisition, DOA, are recorded.

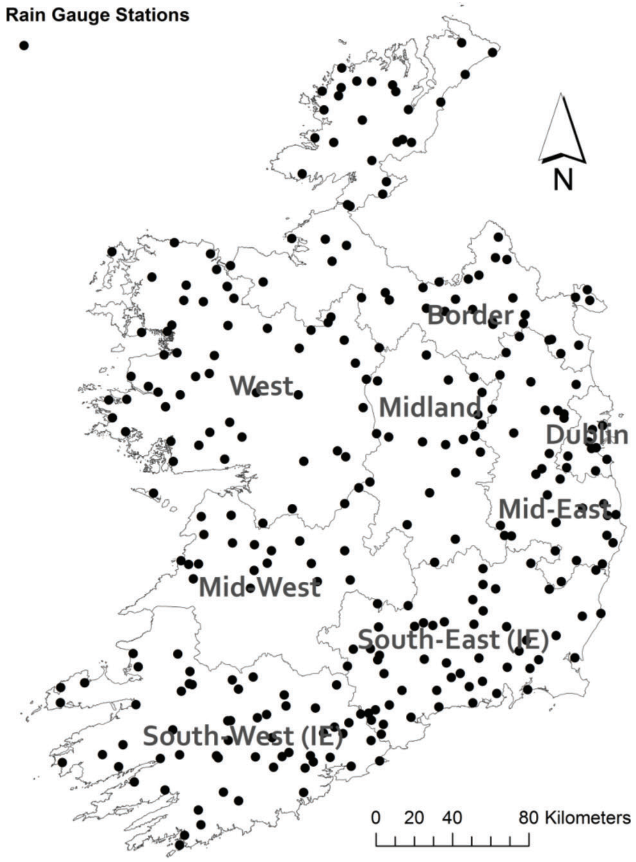

Figure 3: Distribution of rain gauge stations used in analysis

All 16-day composites for the period January 1- May 15 2008-2012 were used. Thus from Jan 1st to May 15th there are 9 Images each year. The farm locations in the study were overlaid on top of the images and the corresponding NDVI score extracted so each farm has 9 NDVI scores each year.

The average NDVI score for each year for each farm and the actual NDVI score at turn out for each farm was also calculated. It is important to note that the NDVI score is uncalibrated, it is related to grass cover amounts but is not a direct estimate of such. A typical NDVI trend for a farm will have NDVI increasing across spring as grass grows from dormancy, with an NDVI of 0.6, to maximum biomass production in mid May with NDVI$>$0.8, at the rate of 0.001 per week.

Explanatory data: Rainfall

Daily rainfall data from the national rain gauge network from Met Eireann was used (Walsh, 2012). The exact number of stations in the network varies from year to year but in this analysis (2008-2012) there were 550 stations of which 301 had complete records and were used in this analysis, see figure 3. Each farm in the sample set was ascribed the average of the daily rainfall recorded at the 3 stations closest to it (mean distance, farm to rain gauge, was 7.5km).

Field experiments in Ireland have shown that soil moisture deficit, SMD, is a predictor of soil damage through poaching (Piwowarczyk *et al.*, 2011). SMD is the interaction of weather and soil. As the soil remains the same over time it was assumed that SMD and thus trafficability would be strongly influenced by recent rainfall intensities. Therefor total rainfall (in mm) in the 16 day period before each satellite acquisition and the number of dry days in the period was calculated for each farm as proxies for SMD and trafficability conditions. The total rainfall in spring and the total number of dry days in spring were also calculated each for year for each farm. Table 1 list summarizes the variables used.

3. Methodology

The sample of farms is not a random one and was not designed to model the distribution of farm response to environmental conditions. The repeated measurements are not equivalent to treatments and are not controlled. It's unlikely our sample and variables capture all affects and any omitted covariate will cause a bias in estimating the effects of the covariates we have included. Using a fixed effects model allows us to control for all fixed differences between farms (location, size of farm, farmer education, soil type *etc.*) within the panel.

The fixed model looks at how variation in TOD (around the mean) changes in response to variation in NDVI and rainfall. In the fixed effect model the intercept is allowed to change between farms but the slope of the response is considered the same across each farm and is formulated as:

$$Y_{it} = \alpha_i + \beta_1 X_{it} + U_{it}$$

- Y_{it} is the dependent variable (TOD) where i = farm (i=1….199) and t = time (t=2008…2012)
- α_i is the intercept for each farm
- X_{it} represents one independent variable (NDVI or Rainfall)
- β_1 is the coefficient for that variable
- u_{it} is the error term.

It should be noted that this model assumes there are unobserved factors that influence TOD that are time invariant. A possible source of non-time-invariant factors could be severe weather in an autumn or policy/advice changes nationally – neither are considered to have occurred during 2008 -2012. A fixed effect linear panel analysis of the variation between years of TOD and environmental variables was carried out. The panel of 199 farms with 5 years of observations (995 observations in total) is balanced. The panel ID variable is Farm ID and the time variable is year (2008-2012). When examining the presence of a seasonal effect, then a year dummy is included.

The focus on inter-annual variation in TOD in response to changing environmental variables, as opposed to the causes of variation between farmers, indicated the use of a fixed effect model. This was confirmed by the application of a Hausmann test strongly suggesting the rejection of a random effects model (F test results

Table 1: Summary of variables used in analysis (Number of Observations 995)

Variable	Mean	Std. Dev.	Min	Max	Description
TOD	60.871	21.686	4	121	Turn Out Day
meanvi	0.762	0.059	0.467	0.866	Average NDVI Jan 1-May 8
totrain	358.972	111.772	123.4	880	Total Rain Jan 1-May 8 (mm)
totdry	63.537	16.622	11	119	Total Number of Dry Days Jan 1-May 8
truevi	0.757	0.066	0.440	0.882	Actual NDVI at TOD
trurain	40.962	28.521	0	184.2	Total Rain 16 days prior to TOD (mm)
trudry	6.587	3.399	0	16	Total number of Dry Days 16 days prior to TOD
totr_1	45.966	43.066	0	269.7	Total Rain Jan 1st-Jan 16 (mm)
totr_17	69.835	37.070	0	246.9	Total Rain Jan 17-Feb 1 (mm)
totr_33	43.053	25.347	0	152.1	Total Rain Feb 2-Feb 17 (mm)
totr_49	37.082	29.960	0	170.8	Total Rain Feb 18-Mar 5 (mm)
totr_65	38.850	21.606	0	139	Total Rain Mar 6-Mar 21 (mm)
totr_81	23.681	16.327	0.2	84.3	Total Rain Mar 22-Apr 6 (mm)
totr_97	40.621	35.635	0	168.5	Total Rain Apr 7-Apr 22 (mm)
totr_113	28.035	24.724	0	99.3	Total Rain Apr 23-May 8 (mm)
totr_129	31.850	22.151	0	140.6	Total Rain May 9-May 25 (mm)
ndvi_1	0.731	0.065	0.463	0.864	NDVI Jan 1st-Jan 16
ndvi_17	0.731	0.067	0.448	0.859	NDVI Jan 17-Feb 1
ndvi_33	0.737	0.069	0.440	0.879	NDVI Feb 2-Feb 17
ndvi4_49	0.748	0.069	0.444	0.882	NDVI Feb 18-Mar 5
ndvi_65	0.763	0.067	0.459	0.885	NDVI Mar 6-Mar 21
ndvi_81	0.780	0.062	0.477	0.893	NDVI Mar 22-Apr 6
ndvi_97	0.796	0.056	0.493	0.895	NDVI Apr 7-Apr 22
ndvi_113	0.810	0.049	0.512	0.895	NDVI Apr 23-May 8
ndvi_129	0.755	0.066	0.440	0.879	NDVI May 9-May 25
dry_1	7.006	3.964	0	16	No. Dry Day Jan 1st-Jan 16
dry_17	4.716	3.127	0	16	No. Dry Day Jan 17-Feb 1
dry_33	6.778	3.087	0	16	No. Dry Day Feb 2-Feb 17
dry_49	7.401	3.403	0	16	No. Dry Day Feb 18-Mar 5
dry_65	5.371	3.453	0	15	No. Dry Day Mar 6-Mar 21
dry_81	8.232	3.221	0	15	No. Dry Day Mar 22-Apr 6
dry_97	7.426	3.532	0	14	No. Dry Day Apr 7-Apr 22
dry_113	8.963	4.538	0	16	No. Dry Day Apr 23-May 8
dry_129	7.644	3.990	0	16	No. Dry Day May 9-May 25

strongly indicated fixed effects over pooled approaches). All non-spatial statistical analyses were conducted in the statistical package Stata 11 (StataCorp, 2009).

The relationship to be examined is illustrated in figure 4, where the NDVI in each 16 day period is plotted against the rainfall in the period for each farm for each year (199*9*5= 8955 points) and colour coded for whether the cattle are turned out (no if the period is before the turn out date that year, yes if after). The relationship is complex but in general the black dots (yes) cluster around low rain, high NDVI.

4. Results

Spatial analysis

Table 2 shows the result the fixed effect panel analysis examining how amounts of grass and rainfall across spring relates to the decision of the farmer to turn out. The within variation R^2= 0.387 (199 farms, 5 years a total of 995 observations). The overall fit of the model is good but many of the variables have a low significance. N.B. when interpreting the variables; the TOD variable is a Julian day , with January 1st as 1, January 2nd as 2 etc., so a low value TOD indicates an early turn out

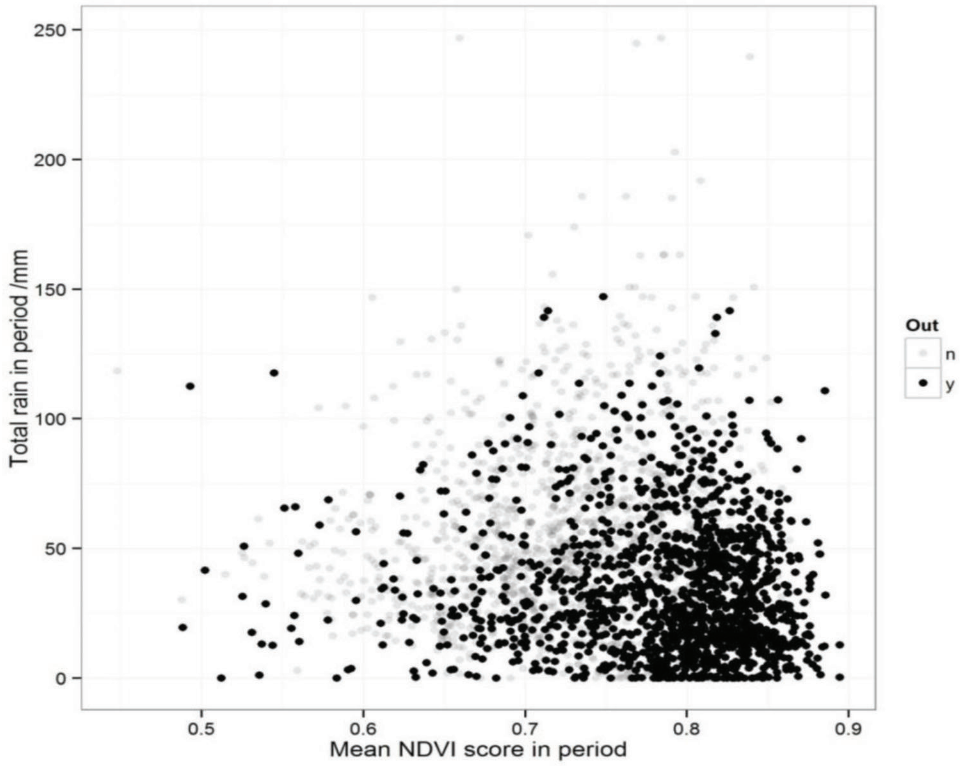

Figure 4: NDVI against rainfall for all observed periods, coded for whether the cattle are turned out (yes or no)

Table 2: Factors associated with turn out date.

Variable associated with TOD	Coefficient (t)	Variable associated with TOD	Coefficient (t)
Total Rain Jan 1st-Jan 16 (mm)	-0.001(0.05)	No. Dry Day Jan 1st-Jan 16	0.238(1.26)
Total Rain Jan 17-Feb 1 (mm)	0.025(1.71)	No. Dry Day Jan 17-Feb 1	0.156(0.60)
Total Rain Feb 2-Feb 17 (mm)	0.008(0.37)	No. Dry Day Feb 2-Feb 17	0.236(1.33)
Total Rain Feb 18-Mar 5 (mm)	-0.019(0.78)	No. Dry Day Feb 18-Mar 5	-0.022(0.10)
Total Rain Mar 6-Mar 21 (mm)	0.009(0.38)	No. Dry Day Mar 6-Mar 21	-0.395(1.88)
Total Rain Mar 22-Apr 6 (mm)	0.109(2.76)**	No. Dry Day Mar 22-Apr 6	0.217(0.87)
Total Rain Apr 7-Apr 22 (mm)	0.023(0.73)	No. Dry Day Apr 7-Apr 22	-0.311(1.37)
Total Rain Apr 23-May 8 (mm)	-0.088(2.64)**	No. Dry Day Apr 23-May 8	-0.279(1.33)
Total Rain May 9-May 25 (mm)	0.015(0.54)	No. Dry Day May 9-May 25	0.045(0.29)
NDVI Jan 1st-Jan 16	-42.132(1.14)	Constant	81.505(5.76)**
NDVI Jan 17-Feb 1	2.005(0.03)		
NDVI Feb 2-Feb 17	-94.435(1.61)		
NDVI Feb 18-Mar 5	-111.586(2.03)*		
NDVI Mar 6-Mar 21	-91.843(1.70)		
NDVI Mar 22-Apr 6	-144.295(1.81)		
NDVI Apr 7-Apr 22	174.002(1.37)		
NDVI Apr 23-May 8	-103.291(1.42)		
NDVI May 9-May 25	380.257(11.54)**		

Observations= 995. Panel ID FARM_CODE=199. Time ID Years=5
Within R^2=0.387 (F=9.57***). Absolute value of t-statistics in parentheses
* $p<0.05$; ** $p<0.01$

of cattle and this is generally desirable; this means negative coefficients will decrease TOD as the variable increases.

Rainfall at End of March is significant, with every extra 10.1 mm of rain in the period increasing the TOD by 1 day. This seems logical, farmers may delay turn out if rainfall is heavy, even if enough grass is present. However rainfall at the end of April is also significant but this time with increasing rain leading to a decrease in TOD, this is difficult to interpret but nearly all farmers will have already turned out by then and we may be capturing a seasonal affect.

Grass growth as indicated by NDVI has less of an apparent influence, NDVI at end of February, when many farmers will be considering turning out, is related such that an early turn out date is more likely with higher grass growth. The NDVI score for Mid-May is significantly related to turnout and this is a seasonal affect, the significance disappears when year dummies are included. The coefficient seems to indicate higher grass in Mid-May is associated with a later turn out date, this is because in a ''good year'', significant biomass is removed by mid-may through grazing and even silage cutting, so high NDVI in May indicates that perhaps spring began slowly. The ''number of dry days'' is not influencing, individually, the TOD. Rainfall and number of dry days were both included to attempt to account for intensity of rainfall. Interaction terms for these variables have been investigated and show no significance in the model performance or make up.

It is clear that multi-colliniarity between variables must be high in this scenario- the grass growth in March is strongly related to grass growth in February and so on. Even rain fall shows a relative pattern of decrease across the spring. To attempt to reduce this affect, the bi-weekly variables were reduced to three single metrics to describe the overall spring; Mean NDVI score Jan1st to May 25th (a high mean NDVI score across spring implies good grass growth), the total rainfall Jan1st to May 25th and the total number of dry days in the same period. We also included 3 metrics to characterise TOD, The NDVI score at actual turn out date, the rainfall in 16 days preceding and the number of dry days in the same period.

Table 3 shows the results of a fixed effect panel analysis on TOD using these variables with and without a year dummy. Without year dummies all the variables are significant with average NDVI strongly influencing TOD. If grass growth over spring is high then turn out dates are early, if spring is wet then TOD is late (3.5 days later for every 100mm of rain). But the number of dry days seems to affect TOD contrary to expectation with TOD later if the number of dry days increases.

At the time of turn out an increase in the number of dry days in the previous 16 days makes TOD earlier (0.46 days earlier for every extra dry day) but so does an increase in rainfall and higher grass growth at turn out is associated with a later date. Some of these contrary results are partially explained when a year dummy is included in the result. We can see that, in comparison with 2008, 2010 is associated with TOD being 4.94 days later and 2012 with TOD being 5.96 days earlier. As a result of including the year dummies total dry days are no longer significant and total rainfall is only just significant at the 5% level.

If the assumption of a framer having a target date is true then this could be picked up with a lagged variable- the previous year's TOD. If farmers have a preference for a TOD regardless of conditions and only change in extremis, using the previous year's TOD allows us to capture this. One impact of using a lagged variable is that 2008 cannot be used as we do not have 2007 TOD.

The inclusion of the lagged variable in the FE model above has little impact. With the lagged variable itself not significant though the overall model R^2 marginally increases and the RMSE goes from 15.3 to 14.3 (see table 4). Note that the year dummy now references 2009 as 2008 data not included in analysis.

A predictive model

The explanatory approach in the previous section can be expanded to look at prediction of TOD knowing current conditions. For the predictive model we can move beyond the fixed effects into a random effects model that incorporates variance between farms. This is important as formally the fixed effects model can only be used to

Table 3: Seasonal and local factors associated with TOD

Variables associated with TOD	Coefficient (t)	with year dummies Coefficient (t)
Average NDVI Jan 1-May 8	-399.312(11.74)**	-357.209(10.70)**
Total rain Jan 1-May 8 (mm)	0.036(6.77)**	0.015(1.96)*
Total number of Dry Days Jan 1-May 8	0.245(4.54)**	0.093(1.60)
Actual NDVI at TOD	323.206(11.26)**	323.439(11.37)**
Total rain 16 days prior to TOD (mm)	-0.079(4.68)**	-0.082(4.84)**
Total number of dry days in 16 days prior to TOD	-0.464(2.84)**	-0.518(3.19)**
Year Dummy		
2009		0.322(0.703)
2010		4.94(2.83)**
2011		1.2(0.83)
2012		-5.962(-4.13)**
Constant	98.246(8.70)**	83.273(6.54)**

Observations=995. Panel ID FARM_CODE=199.Time ID Years=5
Within R^2=0.323 (F=35.59***), with Year Dummies R^2=0.363 (F=24.91***)
Absolute value of t-statistics in parentheses
* $p<0.05$; ** $p<0.01$

Table 4: Seasonal and local factors associated with TOD in a fixed effects model with a lagged TOD variable added

Variables associated with TOD	with year dummies Coefficient (t)
Average NDVI Jan 1-May 8	-344.342(9.55)**
Total rain Jan 1-May 8 (mm)	0.012(1.34)
Total number of Dry Days Jan 1-May 8	0.037(0.54)
Actual NDVI at TOD	301.930(10.34)**
Total rain 16 days prior to TOD (mm)	-0.072(3.82)**
Total number of dry days in 16 days prior to TOD	-0.227(1.16)
TOD_lag	0.017(0.5)
Year Dummy	
2010	4.57(2.77)**
2011	0.930(0.63)
2012	-6.475(-3.75)**
Constant	83.841(6.13)**

Observations=796. Panel ID FARM_CODE=199. Time ID Years=4
Year Dummies R^2=0.382 (F=22.51)
Absolute value of t-statistics in parentheses
* $p<0.05$; ** $p<0.01$

Table 5: Seasonal and local factors associated with TOD in a random effects model with a lagged TOD variable added

Variables associated with TOD	i) Coefficient (t)	ii) with lag Coefficient (t)
X Coor	-0.0000141(-1.03)	-0.00000677(0.77)
Y Coor	0.0000627(7.00)**	0.00000924 (1.56)
Dry Soil Dummy	-4.230995 (2.97)**	-2.581223(3.02)**
Average NDVI Jan 1-May 8	-503.589(23.22)**	-375.260(17.86)**
Total rain Jan 1-May 8 (mm)	0.038(7.4)**	0.0313 (6.37)**
Total number of Dry Days Jan 1-May 8	0.250(6.56)**	0.130(3.92)**
Actual NDVI at TOD	427.206(22.73)**	313.487(16.84)**
Total rain 16 days prior to TOD (mm)	-0.102(-5.95)**	-0.097(5.53)**
Total number of dry days in 16 days prior to TOD	-0.489(3.01)**	-0.199(1.18)
TOD_Lag		0.4868 (20.9)**
Constant	94.168(10.83)**	66.239(9.63)**

Observations=995. Panel ID FARM_CODE=199. Time ID Years=5
Overall R^2=0.589, with TOD lag
Observations=796. Panel ID FARM_CODE=199. Time ID Years=4
R^2=0.745
Absolute value of t-statistics in parentheses
* $p<0.05$; ** $p<0.01$

infer relationships of within the sample where as a random effects model allows for inference and thus prediction from the larger population from which the sample was drawn (due to the assumption of a normal distribution to the residual term). This allows us to include x and y location and soil type (dummy variable for well drained or poorly drained recorded in the NFS) in our model as a between farm affect The result of the random effects models (maximum likelihood) also show the much bigger impact of using the lagged TOD variable, table 5

This random effects model, shows the influence of location and soil drainage found in other studies with Dry soil associated with TOD being 4.5 days earlier and northernliness (y coordinate) leading to TOD being 1 day later for every 16km north. The other terms are similar to the FE coefficients. If the TOD_lag is introduced we can see the R^2 fit of the model increase significantly but the x and y coordinates are no longer significant as the TOD variation is captured in the lagged variable. This model allows us to predict a TOD for the NFS farmers using the equation:

$$TOD = 66.236 + DSM.(-2.581) + meanndvi.$$
$$(-375.260) + totr.(0.0313) + totdry.(0.13) +$$
$$truendvi.(313.487) + trurain.(-0.097) +$$
$$TOD\_lag.(0.487)$$

Predicted TOD and actual TOD for the period are shown in figure 5. Note that in the TOD_lag model the constant value (66.2) is 28 days earlier than the model without the lagged variable (94.2). The lagged coefficient is 0.487. If we apply the coefficient to the mean TOD we get 29.7 days, this is not a coincidence as the lagged variable within the random effects model is moving variation from the alpha term fixed in time into a time variant variable. It would be preferable to have an independent test set to test this predictive power fully.

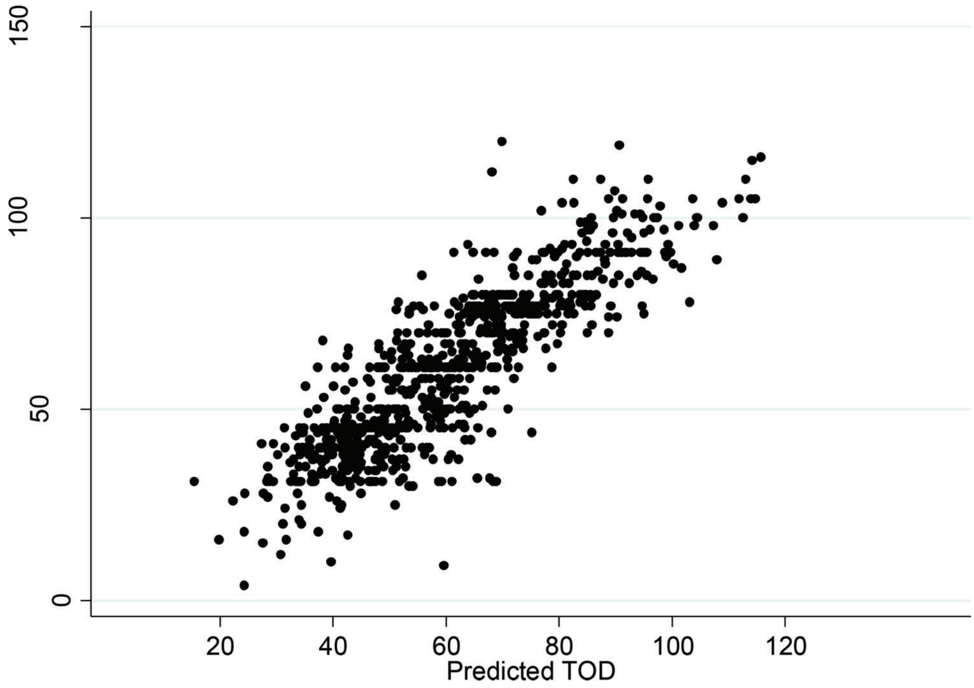

Figure 5: Predicted TOD against actual TOD (Julian days) for the model data

5. Discussion

Better overall growth in spring seems to be related to earlier turn out dates but an opposite, equal effect is present locally at turn out, more grass on the farm at turn out is related to a later turn out. It is important to remember the strong seasonal effects; grass grows over time, all things being equal, the longer you wait the more grass there will be and less rain will fall as spring turns to summer. However we have hypothesised that farmers have a target grass level at their farm they want to achieve before turn out.

Farmers respond to overall conditions, to a ‘‘bad’’ spring, like 2010, or to a ‘‘good’’ spring like 2012 and adjust their turn out dates but they do not do so optimally, there is a lag in the response, shown by the positive relationship between NDVI at turn out and TOD. In a good year they are letting the grass grow too far before responding quickly enough to a good spring.

If the response of farmers to good conditions was optimal then the coefficient of NDVI at turn out date would be zero in table 4, all else being equal the amount of grass at turn out on the farm should always be the same. The size of the coefficient is an indicator of how farm from optimal the group of farmers are.

The increase rainfall at turn out being related to early TOD could be a seasonal effect, there is more rainfall early in the season and could indicate that farmers are more driven by available grass growth than soil conditions when considering an early turn out. A soil drainage dummy was included in earlier analysis and did not prove significant. The increase in the number of dry days at turn out being associated with earlier turn out is however an indicator that farmers are responding to local weather conditions when deciding to turn out. An interaction term between rainfall and dry days at turn out was investigated and not found significant.

It is likely that better knowledge of soils and drainage on the NFS farms would add considerable nuance to the picture of weather conditions and turn out date as would a more sophisticated handling of the rainfall data (the number of days over which to sum rain to get a picture of soil trafficability would vary considerably by soil type).

Table 6: Comparison of the internal predictive capabilities of the four models

Model	R^2 predict	RMSE on prediction (days)
Fixed Effects	0.501	15.32
FE+ TOD lag	0.549	14.3
Random effects	0.581	14
RE+TOD lag	0.742	10.8

Our picture of NDVI and growth is also crude but better resolution satellite imagery, and better geolocation of the NFS farms (mapped parcels rather than location of farmhouse) will allow us in the near future to be able to characterise the grass growth at field scale rather than in the generally location of the farm.

The predictive capabilities of the model seem good, at least for the NFS sample, in the absence of previous TOD for all farms then any national TOD prediction will depend upon the random effects coefficients in table 5. A comparison of the predictive capabilities is shown in table 6. The RMSE of 10.8 days when compared to an intra-farm average TOD variation of 25 days suggests this model could provide useful high resolution measurements of impact on TOD of current spring conditions on the farms in the NFS and wider.

6. Conclusion

Farmers are responding to general springtime growth conditions and measurements of NDVI over spring by satellite can quantify the size of the response on turn out dates at the farm. Nationally, on average, turnout date gets a day later for every 16km further north of the south coast. Farmers seem to have a lag in their response to good conditions, waiting until there is more grass than is normal at their farm before turning out and turning out early in poor years to low levels of grass cover. The number of dry days in the run up to turning out and the total amount of rainfall are associated with changes in TOD.

National seasonal effects dominate over local weather conditions and for every extra 0.01 in the average spring NDVI value score at the farm location turnout was 3.6 days earlier but this early turnout was associated with a higher actual NDVI on the day, that showed effectively the turn-out was 3.3 days later than it could have been. As 0.01 NDVI equates to a week's growth typically it showed that farmers do respond to good conditions but not as quickly as they could. The rainfall data implied that soil condition was of secondary importance to grass levels, especially in poor springs and year dummies showed that seasonal effects are national- 2010 was a cold spring caused turn out dates to be 4.6 days later, whereas the warm spring of 2012 allowed cattle to be turned out 5.6 days earlier.

The inertia in decision making around a preferred date was shown by using the previous year's TOD in the model. By using this along with the other data we can accurately predict when Turn out occurs with a RMSE of 10 days (compare to the average on farm inter-annual range of dates of 25 days).

This work has quantified some of the real-time factors that farmers do take into account when making decisions. It's also shown there is still considerable capacity for increased exploitation of grassland resources within current management systems and stocking densities.

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