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Short running title: Modelling irrigated chlorophyll production

Modelling irrigation and fertiliser use for chlorophyll production

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Abstract

Chlorophyll is a natural colouring extract used extensively in the food and pharmaceutical industries. In Europe, most chlorophyll is produced commercially from rainfed grassland production in eastern England. This paper describes a biogeochemical modelling study to assess the potential yield benefits associated with switching from rainfed to irrigated production. The research is in response the impacts of recent summer droughts on yield coupled with risks regarding climate change, rainfall reliability and long-term viability of rainfed production. The Denitrification-Decomposition (DNDC) model was calibrated and validated using multiple field data (n=47) from 2000 to 2009 for a tall fescue grass (*Festuca arundinacea)* to simulate a range of irrigation and fertilizer management regimes on yield (annual and individual yield per cut). For chlorophyll production, a schedule combining 300 mm yr^{-1} irrigation with 300 kg N per ha was shown to provide the highest average yield (an uplift of +62% above current levels). Switching from rainfed to irrigated production could also potentially halve (54%) current levels of fertilizer application. The implications for reducing environmental impacts from nitrate leaching are discussed.

Keywords

Crop model; grass; irrigation scheduling; water; yield.

Introduction

In most countries, grasslands constitute a significant component of agricultural land use. In Europe they account for approximately 184 × 10^6 ha and represent more than a third of the total agricultural cropped area (Smit *et al.* 2008; Török *et al.* 2011). Although predominantly grown for animal grazing, grass is also grown for the extraction of sweeteners, paper, pulp and combustible carbohydrates (Fowler *et al*. 2003). In England, tall fescue (*Festuca arundinacea)* is grown to produce chlorophyll, the natural green pigment in the cells of plants responsible for absorbing light energy for photosynthesis. This is a highly valuable extract used in the food and pharmaceutical industries as a natural colorant. Nettle, alfalfa, spinach, and lucerne are also used, but grass is the most widespread source for chlorophyll extraction in Europe (Mortenson 2006). Pure chlorophyll is difficult to isolate so the commercial product contains other pigments including fatty acids and phosphatides, and known as 'technical chlorophyll'. Extraction is only economically viable when the chlorophyll content is over a certain threshold. It is extracted using acetone, ethanol, light petroleum methyl ethyl ketone and dichloro methane, and known commercially as 'E140'. This code is part of a set approved by the Food Standards Agency for use within the EU (E numbers 140 to 149 constitute colouring additives) according to the European Scientific Committee for Food (FSA 2010; Igoe and Huim 2001). Although E numbers are perceived to be 'additives' chlorophyll is in fact a natural colorant used to maintain the food colour expected or preferred by consumers, for example, in confectionary, chewing gum, ice cream and soups. The demand for chlorophyll as a natural food dye is growing steadily in response to consumer concerns regarding food safety and the use of synthetic dyes.

Due to its humid climate, most crop production in England is rainfed with supplemental irrigation used only on high-value vegetables, potatoes and soft fruit (Knox *et al.* 2010). Irrigation helps to improve yield (t ha^{-1}) and quality (£ t^{-1}) with consequences for revenue (£ha^{-1}) and provide the quality assurance demanded by processors and supermarkets (Knox *et al.* 2009). In contrast, only a very small proportion (<1%) of grassland is irrigated, mainly to support animal production on drought prone soils in dry summers in lowland areas. All grassland for chlorophyll production is rainfed but recent droughts have highlighted the impacts of low rainfall on yield and inefficient nitrogen uptake. Climate change threatens to exacerbate the situation due to changes in rainfall patterns, greater climate uncertainty and reductions in summer rainfall (Christierson *et al.* 2012; Daccache *et al.* 2011). Rising fertilizer costs are also having major impacts on the economic viability of rainfed production. Supplemental irrigation could help offset the impacts of rainfall variability, deliver more reliable and higher yields and reduce the environmental impacts associated with nitrate leaching after heavy rainfall events. However, despite extensive evidence in the scientific literature on grassland agronomy, most grassland irrigation research focusses on maximizing turf quality for landscape or amenity use (e.g. Aamlid *et al*. 2015; Strandberg *et al.* 2012) or on studying the impacts of climate change (e.g. Höglind *et al.* 2012).

According to UK government fertilization recommendations (Defra 2010), the most common grassland N application rates typically vary between 200 and 340 kg N ha^{-1} $year^{-1}$. Under intensively grazed conditions to support high stocking rates for sheep and beef production, as well as for high milk yields in dairy producing farms, annual recommendations can reach 370 kg N ha^{-1}. Fertilizer practices for grassland chlorophyll production typically involve N applications after each cut to ensure a higher chlorophyll content as N leaf content has been correlated to chlorophyll readings in tall fescue (Errecart *et al.* 2012). But nitrate is highly soluble and can easily be leached from agricultural soils due to excess rainfall and irrigation, leading to polluted ground and surface water, causing eutrophication and drinking water contamination. As the leached fraction is directly related to the applied rate, leaching could potentially be reduced by applying smaller, more frequent doses and managing soil water inputs more carefully, without impacting on yield. This paper describes a study to assess the yield impact of different irrigation and fertilizer regimes in grassland chlorophyll production, and the implications for leaching risk. It has broader international relevance to lowland areas where rainfed grassland production is at risk from changes in rainfall distribution and where supplemental irrigation may become more important in the future under a changing climate.

Materials and methods

In summary, a crop growth model was used to assess the impacts of different water and fertilizer regimes on grass yield, using historical field data for a farm in Lincolnshire, England. Annual and individual cut grass yields were simulated using the Denitrification-Decomposition (DNDC) model. This process oriented biogeochemical model was first used to simulate greenhouse gas emissions from agricultural soils (Li *et al.* 1992), then later expanded to predict crop growth, yield, nitrate leaching and the soil buffering effects of ammonium (Li *et al.* 2006; Farahbakhshazad *et al.* 2008). Detailed historical yield data for multiple individual fields from 2000 to 2009 were used to calibrate and validate the model, and statistics used to assess model performance and goodness of fit. The DNDC model was then used to simulate the impacts and sensitivity of different irrigation and fertilizer regimes on yield, to identify the most appropriate for maximizing productivity and minimizing leaching risk. A brief description of the study site and crop modelling is given below.

Site description

The study site was at Blankney, Lincolnshire (53°6′, 0°27′, 45 m a.s.l.) the only farm in Europe involved in commercial chlorophyll production. On average, 6000 tonnes of grass are harvested (3000 tonnes dry matter) annually to produce approximately 15 kg chlorophyll. In England, the growing season typically extends from early April to late September with the warmest months in July and August (mean T_{min} 11°C and T_{max} 20°C). Rainfall varies from between 30 to 80 mm per month and average reference evapotranspiration (ETo) estimated using the FAO Penman Monteith method ranges from 3 to 4 mm per day. Daily meteorological data (rainfall, maximum and minimum temperature) and field records (fertilizer application, dates for grass cutting and yield) were provided for 2000 to 2009. The agricultural soils on the farm, especially those used for grassland production were assumed to be homogeneous and defined as dry grassland/pasture. Two soil tests (each with three samples) were carried out to assess soil texture and pH. Soil texture assessment followed the National Soil Resources Institute method and revealed that the soil was a loamy sand. The pH test on the soil samples was based on British Standard BS ISO 10390:2005 and showed an average pH of 8.01.

Model description

Crop models help simplify reality to simulate a range of elements, factors and interactions that affect crop-environment relations. They are powerful tools to help study the effects of local environment conditions (wet and dry periods) and changing climate and management practices (e.g. irrigation schedule, fertilization application) on crop development and yield response, and thus support management changes and/or recommendations (Topp and Doyle 2004). Specific simulation models have been developed for pasture and grassland production including GRASIM (Mohtar *et al.* 1997), CLASS PGM (Vaze *et al.* 2009) and GRAZEGRO (Barrett *et al.* 2005) although most have been developed to assess grazing productivity. The GRASIM (GRAzing SImulation Model) and CLASS PGM models simulate the interaction between pasture plants, environmental and soil conditions and grazing animals based on physiological characteristics. GRASIM predicts grass nutritional quality and allows for cattle feeding simulation. It also simulates plant growth under partial harvest conditions, predicts drainage and leaching and evaluates stocking rates (Mohtar *et al.* 1997). The CLASS PGM model has been used to simulate grazing management practices (Vaze *et al.* 2009) and generates daily soil hydraulics, dry matter, leaf area index (LAI), total ground cover and root biomass outputs. GRAZEGRO (Barrett *et al.* 2005) is also based on plant physiology processes to simulate growth response to nitrogen and nitrogen cycles. It has been calibrated for UK ryegrass and Timothy cultivars. It predicts organic matter digestibility and crude protein present in grass. Although specific grass crop simulation models have been calibrated for UK conditions, for this study the DNDC model (Li 2000) was deliberately chosen. This is because it allows for irrigation, fertilization and tillage practices to be simulated and is unique in that it allows for modelling the effects of repeated grass cuts, since biomass and chlorophyll content depend on the frequency and timing of individual cuts. A brief description of the DNDC model is given below.

The DNDC model has been described by Gopalakrishnan *et al.* (2012) as a complex model for simulating nitrogen and carbon cycles in soil (Li *et al.* 1992), developed to predict N_2O fluxes from arable soils and later extended to agro-ecosystems. The model has two main components; the first involves the soil, climate, and crop growth components, as well as decomposition sub-models. It predicts soil physical and chemical conditions (temperature, moisture, pH, and red-ox potential) and generates substrate concentration profiles. The second component consists of three (nitrification, denitrification, and fermentation) sub-models to predict emissions of ammonia (NH_3), nitric oxide (NO), nitrous oxide (N_2O), dinitrogen (N_2), carbon dioxide (CO_2), and methane (CH_4). The model reproduces the crop physiological processes (i.e. phenology, photosynthesis and respiration, assimilate allocation, nitrogen uptake, rooting processes and leaf area index) and can simulate stress induced by either insufficient water and/or nitrogen. Internationally, the DNDC model has been used recently to estimate greenhouse gas emissions under different farming systems, for example in winter wheat-maize rotations in China (Li.*et al.* 2010) and in different management scenarios across varying agroclimatic regions in Canada (Smith *et al.* 2010). It was also used for yield simulation of miscanthus and switchgrass in Illinois, USA (Gopalakrishan *et al.* 2012). DNDC works on daily basis estimating crop requirements, uptake and growth based on environmental conditions. It requires field location (latitude and Hemisphere), rainfall, maximum and minimum temperatures. Nitrogen in the form of NH_3 is present in rainfall and in the atmosphere. Rainfall represents an important input in the nitrogen balance of ecosystems. Therefore the model permits changing the annual average nitrogen concentration in rainfall as well as the atmospheric NH_3 concentration. Information on land-use type (upland crop field, rice paddy field, moist grassland/pasture, dry grassland/pasture and wetland), soil texture, bulk density and pH are also required. Crop management practices including fertilization, irrigation, tillage, manure amendment, weed control, flooding, cutting and grazing also have to be specified.

Model parameterization

Model parameterization was first undertaken to account for local soil and climate conditions. Default values for field capacity, permanent wilting point, hydraulic conductivity and porosity are provided, depending on local soil texture, but specific data for bulk density and pH are required. The initial soil organic carbon (SOC) at the soil surface also needs to be defined. Six soil samples from two representative fields were collected from the study site to assess soil pH. Soil tests showed an average pH of 8.096 (SD 0.042). Published typical values for a loamy sand for bulk density, initial soil organic carbon (SOC), NO_3 and NH_4^+ were used. Historical annual and individual cut yields for fescue grass (*Festuca arundinacea)* for 47 fields were provided, as well as farm management data relating to soil and crop husbandry (average cutting dates, average fertilization dates and doses, and nitrogen sources). These were used to parameterize the model. Other crop inputs found in the literature included root, leaf, stem and grain biomass fraction and C/N ratio, thermal and water requirements, maximum yield, root maximum depth and stem height. Management practices such as fertilization (dates, doses and product), irrigation (date and depth), tillage (date and depth), manure amendment, weed control, flooding, cutting and grazing were used. Physical analyses and published data from the scientific literature were used to parameterize and better define the soil, crop and atmosphere properties. Default values for atmospheric background concentrations of NH_3 (0.06 ug N m^3) and CO_2 (350 ppm) were used, with data from Neal *et al.* (2004) used for the average N concentration of rainfall. Data by Gaborcik (1994) were used to define suitable crop parameters. In order to simulate farm management practices, the typical crop husbandry practices relating to fertilization were assumed for all fields. Six fertilizer applications were defined, the first in March, and others shortly after each cut (Table 1). The fields were not manured. No irrigation was applied during the simulated growing season. Modelled individual cuts (15 April, 15 May, 1 July, 25 August, 30 September and 5 November) were based on the average reported dates from 20 years farm records for 47 fields.

Model calibration and validation

The DNDC model was calibrated using the field data from 2001-2005, and an independent dataset (2006-2009) then used for validation. The parameters fixed following model calibration are shown in Table 2. Climate, soil and the crop parameters were fixed at the calibration process, and some crop characteristics – thermal degree day, and water demand - were adjusted at validation. To assess bias in the modelled versus observed yields, the model outputs were statistically analysed. Jacovides and Kontoyiannis (1995) recommend combining t-statistics with the mean bias error (MBE) and root mean square error (RMSE) to assess model performance. The RMSE provides information on the short-term performance of the model by allowing comparison of the actual differences between modelled and observed values. The smaller the RMSE value, the better the model performance. However, this test does not differentiate between under and over-estimation. The MBE provides information on the long-term performance of the model. A positive value gives the average amount of over-estimation in the modelled yield values and vice versa; the smaller the absolute value, the better the model performance. The t-statistic was also calculated, whereby the simulated values are deemed not to be statistically significantly different from the observed values if the calculated *t* values are lower than the critical *t*-value. The following equations were used:

$$RMSE=\left(\frac{1}{N}\sum_{i=1}^{N}d_i^2\right)^{\frac{1}{2}} \qquad [1]$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N} d_i \qquad [2]$$

Where N is the sample size and d_i is the difference between i^{th} simulated and i^{th} observed values.

The observed and modelled annual yields (kg DM ha^{-1}) for the calibration and validation periods are summarized in Figure 1. Visually, for most years, the modelled yield values compared well to the average observed yield and were within ±1 SD (as shown by the error bars), except in 2006 and 2009, which were particularly dry in the local area. Conversely, in some years, the modelled and observed average yields were very similar (2002, 2004). In each year, the observed yields showed wide variation, reflecting soil and crop management differences across a large number of fields studied.

The statistical analyses are summarized in Table 3. For both calibration and validation, the RMSE values (1099 and 1719 kg DM ha^{-1}) confirmed a good level of model performance. For both modelled periods, the RMSE values were also considerably lower than the average standard deviations of the observed field measurements (SD_o). The low positive MBE value (247 kg DM ha^{-1}) for model calibration indicated a small, but systematic over-estimation in annual yield. The equivalent value (584.4 kg DM ha^{-1}) for validation reflects a higher degree of yield over-estimation. However, overall, the mean difference between the simulated and observed mean yields was small (<7%) and since the calculated t values were less than the critical t values (for both calibration and validation), the differences between the simulated and observed annual yields were not statistically significant ($P < 0.05$). Differences between the predicted and observed yield include uncertainty in management practices and the intended end use for the grass; further explanation is provided in the discussion.

Irrigation and fertilizer modelling

The DNDC model was used to simulate the impacts of a range of alternate irrigation and fertilizer management scenarios on grass yield. The modelled outputs were compared against a 'baseline' representing current farm practice. For each model run, 5 years (2001-2005) climate data were used and the average annual yield (sum of stem, leaves and grain) calculated. The individual grass cuts were simulated using the average cutting dates reported by the farm. Fertilizer applications were modelled according to reported farm practices. The first simulated fertilizer application was in March, with the following 5 doses then occurring 5 days after each grass cut. For irrigation, applications were scheduled on fixed dates in each simulated year (20 May, 20 June, 10 July, 30 July, 20 August and 20 September). Scenario 1 represented a 'rainfed only' situation with no addition of nitrogen fertilizer. Scenarios 2 to 9 considered only the effects of different irrigation (total depths applied) on yield. The total irrigation depth applied varied from 0 to 480 mm, distributed over 6 applications, for a water amount per application ranging from 0 to 80 mm. Scenarios 10 to 15 simulated the effects of different nitrogen fertilizer regimes but under 'rainfed' conditions, with the total dose varying from 0 to 750 kg N ha^{-1}. Scenarios 16 to 22 provided a combination of irrigation and fertilizer treatments. The total annual irrigation depth was fixed (300 mm) but with the doses of fertilizer ranging from 60 to 750 kg N ha^{-1}.

Results

A summary of the modelled impacts of different irrigation and fertilizer treatments on annual grass yield, compared to the 'baseline' current farm practice, is given in Table 4. As expected, the lowest yield (−20% variation from baseline) was simulated under the 'rainfed only' scenario with no nitrogen fertilizer application - not representing realistic practice, but rather to construct a crop response curve. Conversely, the highest yield (+64%) was achieved with a total annual irrigation application of 300 mm and a total nitrogen fertilizer dose of 750 kg N ha^{-1}. However, the greatest incremental yield increase occurred between 60 and 180 kg N ha^{-1} (scenario 16 to 17). Beyond this point, the yield response slowed dramatically. Based on crop modelling, the optimal management strategy appears to be one that combines a total irrigation application of 300 mm (6 × 50 mm), with a total nitrogen fertilizer dose of around 300 kg N ha^{-1} (6 × 50 kg N ha^{-1}). However, clearly in practice there is a delicate balance to be struck between applying the right amount of water at the right time (irrigation scheduling) matched against the timing of fertilizer application (dose and frequency) to maximize yield response whilst aiming to minimize any negative environmental impact (drainage and nitrogen leaching). These results agree with the literature. Holmes (1989) recommended applications of 380 to 610 kg N ha^{-1} for grass grown in the UK, and Kantety *et al.* (1996) showed that tall fescues' maximum yield was produced, when applying annual doses of 248 kg N ha^{-1}.

Figure 2 shows, for example, the impacts of different irrigation applications on drainage, assuming no fertilizer application. Maximum yield is reached with an annual irrigation application of around 300 mm. Any excess beyond this leads to a plateau in yield. However, as total irrigation application increases, so too does annual drainage. In the absence of any residual nitrogen in the soil this could lead to aquifer recharge which itself would be beneficial, although it would be highly inefficient in terms of irrigation use (Knox *et al.* 2012). Hence, if a decision to switch from rainfed to supplemental irrigation production is made then it is important to know what the potential yield (and environmental) impacts might be, and what levels of irrigation and fertilizer are likely to generate the highest yield. Figure 3 shows the yield response to varying nitrogen applications under both rainfed and irrigated conditions (assuming an annual application of 300 mm). The yield between the two rainfed and irrigated production systems are markedly different. The maximum yield for the irrigated crop is predicted with a total fertilizer application of 300 kg N ha^{-1}, compared to 180 kg N ha^{-1} for the rainfed crop; however, with irrigation a yield of 12300 kg DM ha^{-1} was predicted compared against 7700 kg DM ha^{-1} for an equivalent rainfed crop. For irrigated production, any fertilizer application in excess of 300 kg N ha^{-1} is shown to lead to a plateau in yield. These figures can be compared against limited international studies. For example, Kantety *et al.* (1996) correlated nitrogen tissue content to chlorophyll meter readings and showed that the maximum yield for a tall fescue was produced when an annual dose of 248 kg N ha^{-1} was applied under field conditions in Alabama (US) and 290 kg N ha^{-1} in a greenhouse environment. In California, a tall fescue grass grown under irrigated conditions with three nitrogen applications (total 195 kg N ha^{-1}) was reported to result in acceptable to good turf quality with the lowest amount of nitrate leaching (Wu *et al.* 2010). However, for chlorophyll production, it is not just the total annual yield that is important, the yield at each individual cut is also critical since this directly influences protein content and hence the amount of chlorophyll available for extraction.

Modelling individual grass cuts

The DNDC model was calibrated and validated using annual yield data, but knowledge of model performance in simulating individual grass cuts is also important for maximizing chlorophyll production. Figure 4 shows the observed and modelled yields for each individual cut (labelled 1 to 7) during 2001 to 2009. There is a growth regeneration period of approximately 30 days between each cut to coincide with fertilizer application (Table 1). Figure 4 shows that there is a much higher degree of variability in observed yield between individual cuts than between individual years (Figure 1) probably due to the impact of variable rainfall and slight differences between cutting dates during the most active growing periods. The DNDC model tends to under-estimate yield for individual cuts between April and May (labels 1 and 2), and over-estimate yield for summer cuts (labels 3 and 4). This is due to a delay in simulated growth with the crop failing to reach its maximum growth rate until the latter part of April. For comparing model performance against observed yields, the average dates for farm cutting were used. However, in practice not all fields are harvested simultaneously, but usually take between 5 and 10 days, which may well account for some of the modelling differences and error.

Discussion

Although the study successfully calibrated and validated a crop model to predict annual tall fescue yield, the methodology does have a number of limitations must be recognised. The main limitation was the model's ability suitability to predict chlorophyll content. The climate input used historical daily rainfall data from a single weather station which was assumed to be spatially representative of all 47 fields. In reality, rainfall varies significantly over even short distances, which would have influenced the accuracy of the simulated yield for model calibration and validation. Soil texture and pH tests were conducted on samples from two fields, which were assumed to be representative of the total cropped area. However, pH is a critical component in maintaining soil fertility; to optimise nutrient uptake and grass sward growth/quality, the optimum pH for grassland should be nearer to 6.0. The pH value used in this study (8.1) was not typical of UK grasslands which tend to be more acidic. Maintaining soil pH at optimum levels would increase microbiological activity in the soil and result in more effective soil nutrient recycling and release. Further modelling of crop yield and its sensitivity to pH would be useful, as well as conducting additional pH sampling across a larger number of field sites to assess in-field pH variability.

Management practices – cuts and fertilization applications – were assumed to take place at the same time for the entire fields; however, in practice some cuts and the following fertilization application suffered of delay due to weather conditions, thus increasing variability in the records and the difference between observed and simulated values. In case of excess in produced grass, a fraction was dedicated for hay and not for chlorophyll production; this split in the purpose of the production was not recorded leading to false lower yields in good years. A number of parameters were estimated due to lack of field data so it is important to assess the sensitivity of the model to certain variables. The effect on yield was studied by varying certain environmental factors. The sensitivity of initial soil conditions including pH and soil NO_3^-, soil activity (N fixation rate and microbial activity), and N concentration in rainfall water were analysed and found to all have a minor (<1%) effect on simulated yield suggesting that the assumed values were acceptable. In the scenario modelling, a fixed irrigation schedule was used, with defined amounts and defined dates. Whilst this is a constraint within the model, it was also not strictly representative of typical farm practice, where irrigation schedules are usually defined on the basis of applying water at a trigger soil moisture deficit (SMD) (fixed amount, variable timing). The modelling also assumed unconstrained water availability, but further research would need to consider the potential yield consequences due to seasonal restrictions in water abstraction for irrigation, and the priorities for grass against other high value crops.

Due to the complexity of each model run and the need to consider individual cuts in each year, the scenario modelling was based on a short climate dataset, but further work could involve using a stochastic weather generator, such as the LARS-WG (Semenov *et al.* 1998) to derive a much longer daily time step dataset for assessing impacts of both natural (historical) and future climate variability. The analysis also ignored the economic viability of switching from rainfed to irrigated production and a detailed cost-benefit analysis of the relationships between irrigation, fertilizer use and yield would be needed to support any irrigation investment. However, the current study does provide indicative data to estimate the potential cost implications in changing fertiliser regimes. For example, assuming £260/tonne for a typical blended granular fertiliser (20:20:10) used for grassland management with 20% N content, a reduction from 600 to 300 kg N ha^{-1} would potentially save a farmer around £390 ha^{-1}.

Finally, a direct relationship between grass yield and chlorophyll content was assumed, but in reality, grass quality is also an important determinant of chlorophyll content, not just yield. Further research needs to focus on the links between protein and chlorophyll content, in order to schedule optimal cutting dates to match biomass production to protein content. Despite these limitations, the study does provide a useful and valuable preliminary assessment of the potential yield benefits and environmental consequences when considering a switch from rainfed to irrigated production.

Conclusions

A crop growth model was calibrated and validated using field data from a commercial farm and used to simulate the yield impacts of different irrigation and fertilizer regimes, compared to an existing rainfed production system. The analysis reveals an optimal combination of nitrogen fertilizer application of around 300 kg N ha^{-1} applied in 5 doses combined with a total annual irrigation application of 300 mm could result in an average annual yield increase of 62%. This would result in an average annual yield of 12.3 t DM ha^{-1} (compared to a current rainfed average yield of 7.6 t DM ha^{-1}) but would importantly also half (54%) the total amount of fertilizer currently applied. The scenario modelling highlighted the importance of balancing irrigation and fertilizer benefits against environmental leaching risks. Although the findings are location specific, there are potentially major implications for other regions, in the UK and internationally where grassland production is rainfed. With climate change, much greater spatial and temporal variations in rainfall are projected, with consequences on soil moisture balances and land suitability. For example, Holden and Brereton (2002) reported that grassland production in Ireland would be subject to much greater risks due to increased summer drought stress. With increased droughtiness, supplemental irrigation would need to compensate for drought, but the survival of existing swards would depend on the economic viability of investment in supplemental irrigation. There would also be major local and regional water resource implications if current lowland grassland areas such as those studied in this paper were to switch from rainfed to irrigated production.

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Table 1 Annual fertilization dates, doses and fertilizer type used at DNDC simulation

Number	**Date**	**Dose (kg N ha^{-1})**	**Fertilizer type**
1	10 Mar	130	Urea/AN
2	20 Apr	120	Urea/AN
3	20 May	110	Urea/AN
4	6 July	110	Urea/AN
5	30 Aug	100	Urea/AN
6	5 Oct	80	Urea/AN

Note: AN; ammonium nitrate.

Table 2 Model parameters and values used to parameterize the DNDC crop model

Crop model parameter		**Value**	**Unit**
Climate	N concentration in rainfall	2	ppm
	Atmospheric NH_3 concentration	0.06	ug N m^3
	Atmospheric CO_2 concentration	350	Ppm
	Annual increase in atmospheric CO_2 concentration	0	Ppm yr^{-1}
Soil	Bulk density	1.5	G cm^3
	Field capacity	0.25	Wfps
	Wilting point	0.13	Wfps
	Clay fraction	0.06	
	Porosity	0.411	
	Macro-pores	No	
	Water logging	No	
	SOC	0.1	kg C kg^{-1}
	Initial NO_3^- concentration at surface	50	mg N kg^{-1}
	Initial NH_4^+ concentration at surface	10	mg N kg^{-1}
	Microbial activity index	1	
	Slope	0	%
Crop	Maximum biomass:		
	Grain	75	kg C ha^{-1}
	Leaf + stem	5250	kg C ha^{-1}
	Root	2175	kg C ha^{-1}
	Biomass fraction:		
	Grain	0.01	
	Leaf + stem	0.7	
	Root	0.29	
	Biomass C/N ratio:		
	Grain	15	
	Leaf + steam	10	
	Root	30	
	Thermal degree day	2500	°C day
	Water demand	550	g water g DM^{-1}
	N fixation rate	1	
	Vascularity	0	
	LAI adjustment factor	3	

Table 3 Summary statistics for DNDC model calibration and validation

Statistic	**DNDC calibration**	**DNDC validation**
Number of years (n)	5	4
Mean yield observed (kg DM per ha)	11067.6	10972.7
Mean yield simulated (kg DM per ha)	11512.3	12287.5
Standard Deviation observed (SD_o)	2088.4	2203.9
Standard Deviation modelled (SD_m)	1009.8	728.7
RMSE (kg DM ha^{-1})	1099.5	1719.7
MBE (kg DM ha^{-1})	247.1	584.4
T-statistic	0.65	1.02
Critical t statistic	< 2.57	< 2.78

Table 4 Summary outputs from DNDC scenario modelling, showing the average annual yield (kg DM per ha) and yield variation (%) with respect to the ‘baseline’ current farm practice

Model scenario	**Nitrogen schedule**	**Irrigation schedule**	**Irrigation depth (mm)**	**Fertilizer (kg N ha^{-1})**	**Mean yield (kg DM ha^{-1})**	**Yield variation (%)**
Farm	109 × 6	0	0	654	7625	±
DNDC scenario						
1	0	0	0	0	6099	−20
2	0	6 × 10 mm	60	0	6406	−16
3	0	6 × 20 mm	120	0	6872	−10
4	0	6 × 30 mm	180	0	7272	−5
5	0	6 × 40 mm	240	0	7601	0
6	0	6 × 50 mm	300	0	7800	+2
7	0	6 × 60 mm	360	0	7807	+2
8	0	6 × 70 mm	420	0	7748	+2
9	0	6 × 80 mm	460	0	7726	+1
10	10 × 6	0	0	60	7149	-6
11	30 × 6	0	0	180	7629	0
12	50 × 6	0	0	300	7629	0
13	75 × 6	0	0	450	7634	0
14	100 × 6	0	0	600	7625	0
15	125 × 6	0	0	750	7626	0
16	10 × 6	6 × 50 mm	300	60	9737	+28
17	30 × 6	6 × 50 mm	300	180	11665	+53
18	50 × 6	6 × 50 mm	300	300	12323	+62
19	75 × 6	6 × 50 mm	300	450	12397	+63
20	100 × 6	6 ×50 mm	300	600	12442	+63
21	109 × 6	6 × 50 mm	300	654	12457	+63
22	125 × 6	6 × 50 mm	300	750	12476	+64

Figure captions

Figure 1 Observed and DNDC modelled grass yield (kg DM ha^{-1}) for the calibration (2001-2005) and validation (2006-2009) periods. Error bars represent ± 1 SD.

Figure 2 DNDC modelled average annual yield (kg DM ha^{-1}) and average annual drainage (mm) for varying irrigation depths (mm) under a 'no fertilizer' scenario.

Figure 3 Simulated average annual yield (kg DM ha^{-1}) for varying nitrogen fertilization (kg N per ha per yr) under irrigated and rain-fed conditions.

Figure 4 Observed and DNDC modelled grass yields (kg DM ha^{-1}) for each individual cut between 2001 and 2009. Error bars represent ± 1 SD.

Figure 1 Observed and DNDC modelled grass yield (kg DM ha^{-1}) for the calibration (2001-2005) and validation (2006-2009) periods. Error bars represent ± 1 SD.

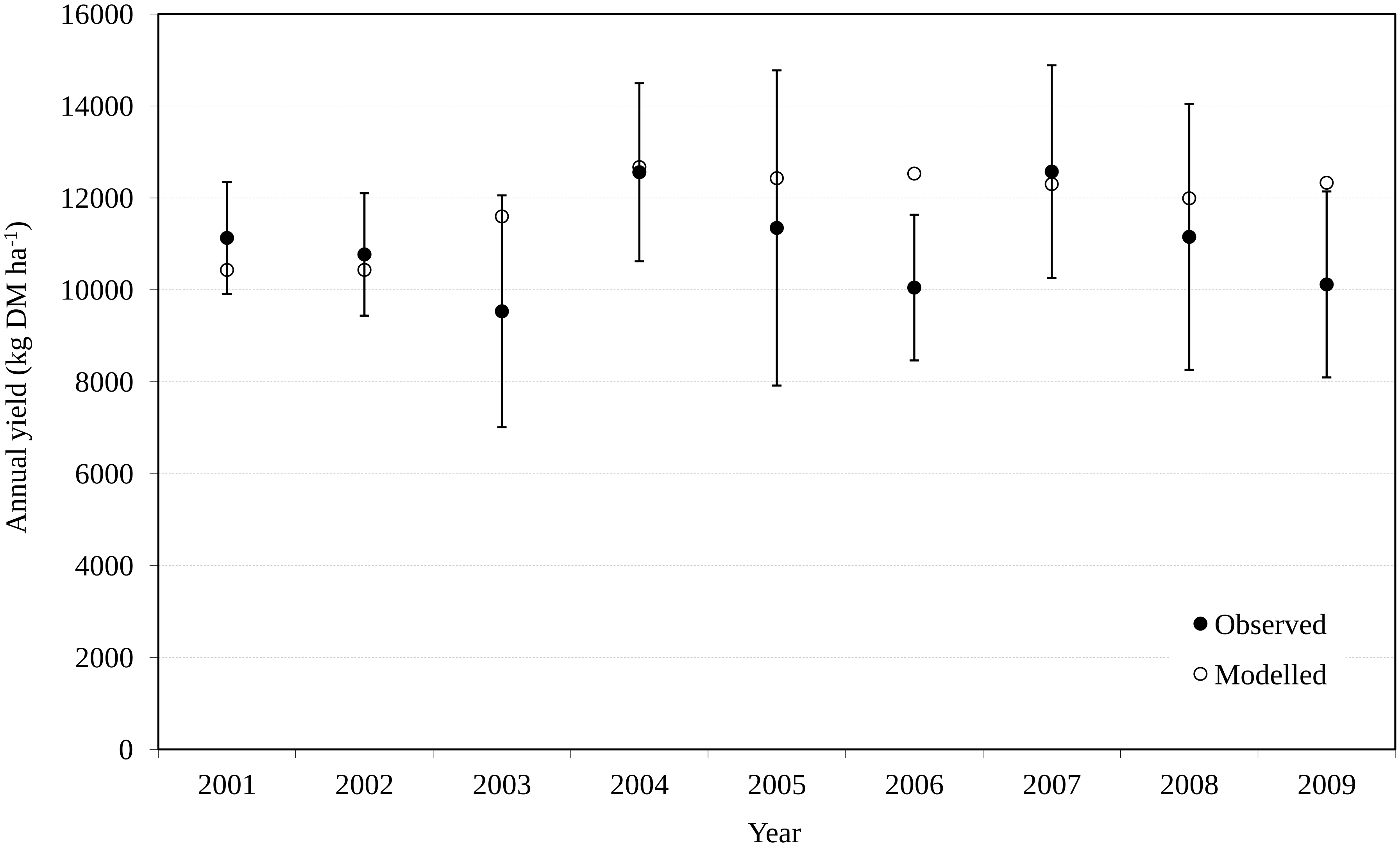

Figure 2 DNDC modelled average annual yield (kg DM ha^{-1}) and average annual drainage (mm) for varying irrigation depths (mm) under a 'no fertilizer' scenario.

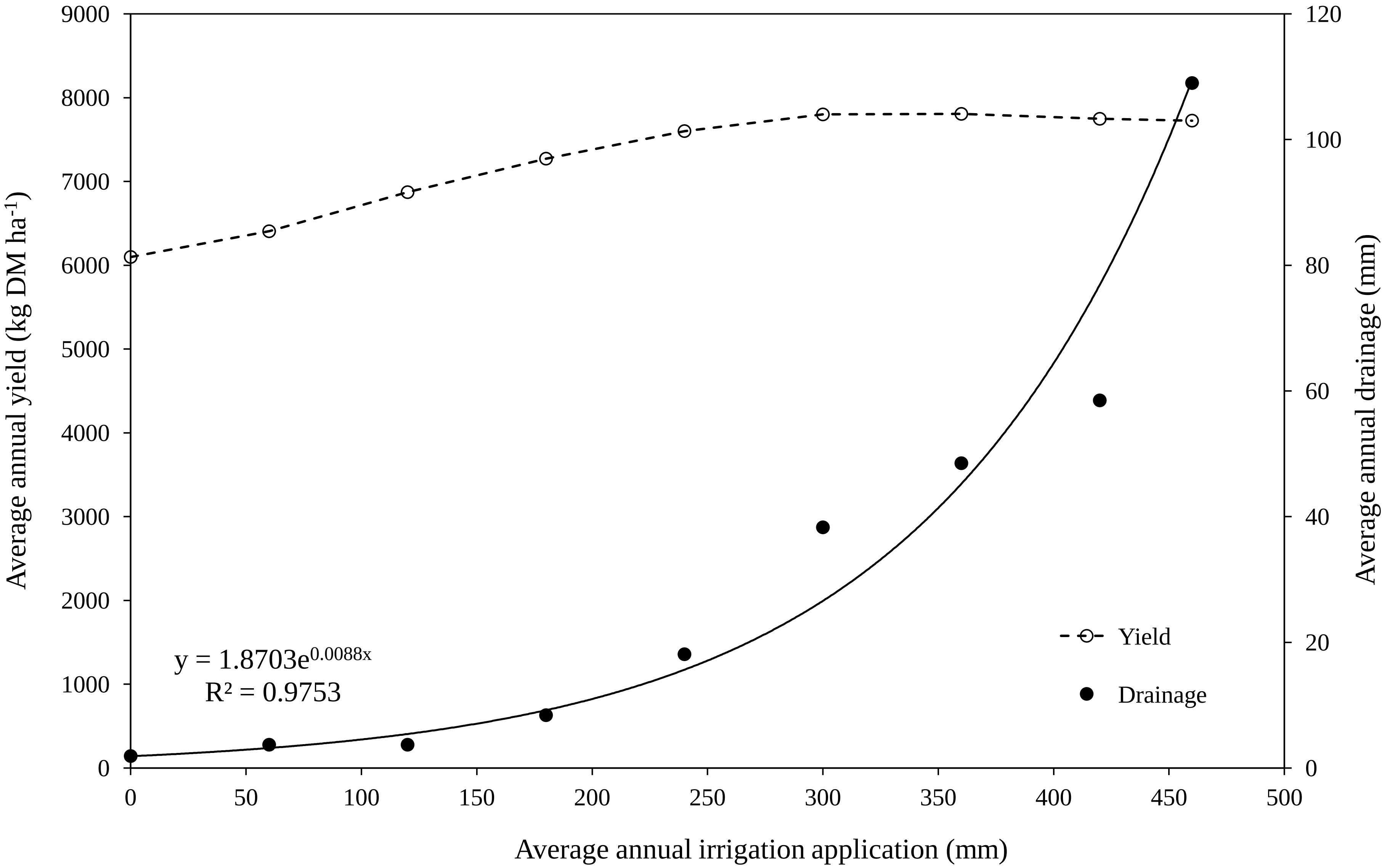

Figure 3 Simulated average annual yield (kg DM ha^{-1}) for varying nitrogen fertilization (kg N per ha per yr) under irrigated and rain-fed conditions.

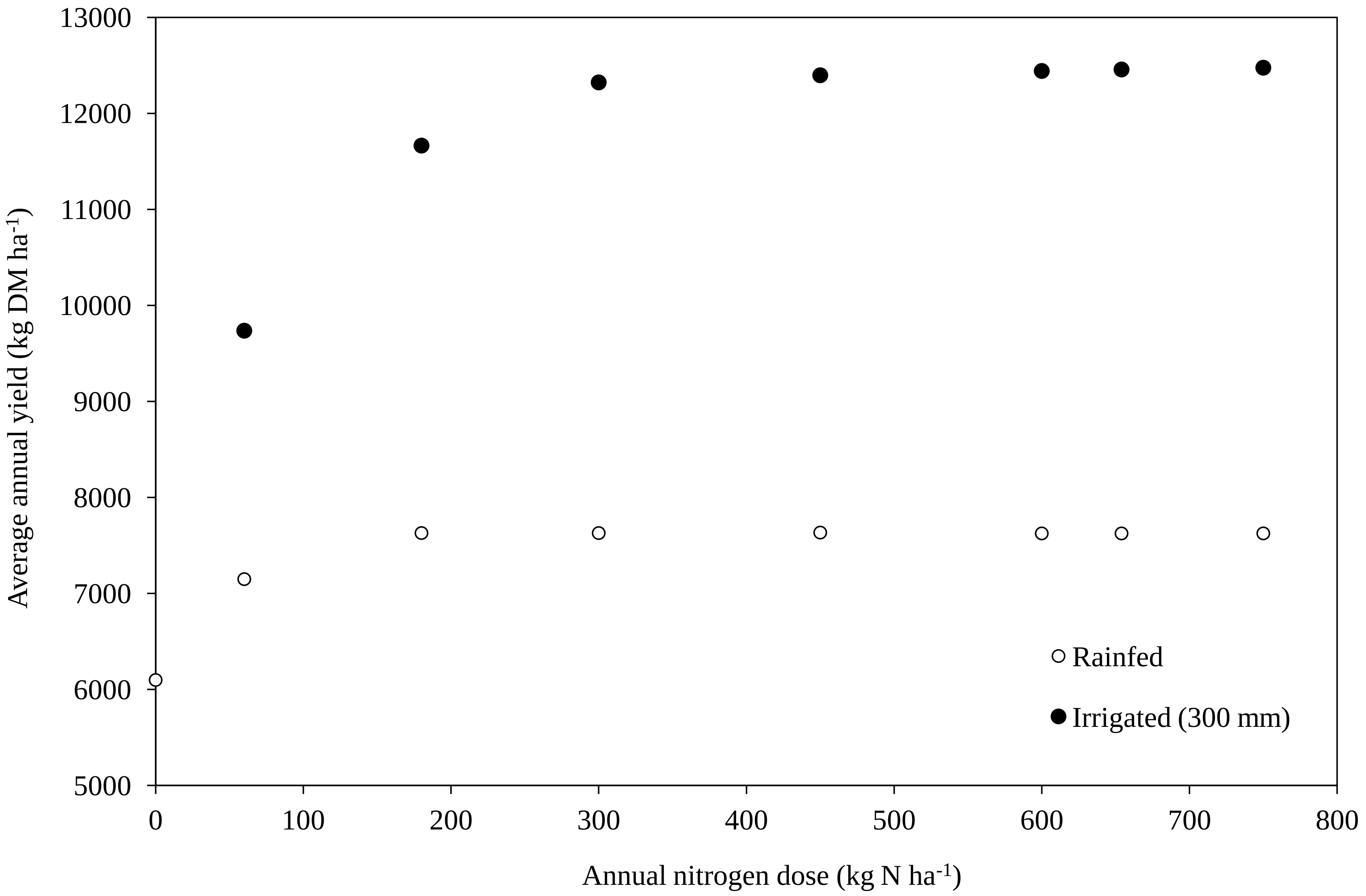

Figure 4 Observed and DNDC modelled grass yields (kg DM ha^{-1}) for each individual cut between 2001 and 2009. Error bars represent ± 1 SD.