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Cost-effective regulation of nonpoint emissions from pastoral agriculture: a stochastic analysis

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Nutrient emissions from pastoral agriculture are a global cause of declining water quality. Their management is complicated through variability arising from climate and soil influences. This paper compares the implications of input-based policies and direct restrictions on leaching to achieve 10 and 20 per cent reductions in nitrogen (N) load, in the context of pasture-based New Zealand dairy farms. The most important mitigation practices on these farms are de-intensification (involving reductions in N fertiliser application and stocking rate) and the application of nitrification inhibitors. A stylised conceptual model, incorporating both sources of variability, is used to identify the implications of alternative policies. Direct restriction of estimated N leaching is the most cost-effective policy to reduce N leaching by 10 and 20 per cent. These results indicate the general insufficiency of input-based mechanisms for water quality improvement, given the low correlation between input use and leaching, possible substitution with unrestricted inputs and their failure to motivate the use of mitigation strategies. Additionally, model output indicates that inherent variability in water quality, mainly due to climate influences, can dominate the benefits of regulatory action in any given year.

Key words: agricultural policy, mathematical programming, natural resource policy, operations research, water management & policy.

1. Introduction

Nonpoint pollution from pastoral agriculture is of growing concern worldwide, with the ongoing nutrient enrichment of ground and surface waters in both developed and developing nations (United Nations Environmental Program (UNEP) 2012). The broad impact of declining water quality on societal values has been broadly identified (Dodds *et al*. 2009), with eutrophication harming property values, recreational use and ecosystem resilience. However, there appears to be little general understanding regarding how producers can be motivated to account for their nutrient emissions, particularly in the context of pastoral agriculture (Monaghan *et al*. 2007a). This difficulty is promoted in the presence of soil heterogeneity and pervasive stochastic processes (Kampas and White 2004). The importance of

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sound regulatory decision making highlights a key role for economic analysis, through which the relative cost of alternative policy instruments can be assessed.

The New Zealand (NZ) dairy industry is of central importance to the nation's economic well-being. Dairy production is New Zealand's largest export industry, with exports valued at $NZ12.1 billion in 2011, which constituted a quarter of all NZ merchandise exports in that year (New Zealand Trade and Enterprise (NZTE) 2012). This industry exports around 95 per cent of its milk production, generating one-third of world dairy trade, and provides employment for around 45,000 people (New Zealand Institute of Economic Research (NZIER) 2010). Moreover, the NZ dairy industry has rapidly expanded over the last 20 years due to its high profitability relative to other land uses, especially sheep and beef farming, with total area farmed increasing by 60 per cent and milk production per ha increasing by 50 per cent over this period (Livestock Improvement Corporation (LIC) 2011).

However, nitrogen (N) leaching from intensive pasture-based New Zealand dairy farms has led to substantial concern regarding its impact on water quality (Doole and Pannell 2012). Dairy cows only assimilate a small proportion of N from feed; thus, around 60–90 per cent is excreted, 70 per cent of this as urine (Monaghan *et al.* 2007a). Urine patches cover around 25–30 per cent of a grazed area in pasture-based systems and contain large amounts of N (around 1 t N/ha). Urea in urine is converted to ammonium, which once oxidised to nitrate by bacteria is easily leached into subsurface water flows and consequently waterways.

Various policies have been investigated with regard to their capacity to regulate N leaching from dairy farms. Livestock density is a key driver of N leaching (Monaghan *et al.* 2007a); thus, restrictions on stocking rate have been proposed as a means to restrict urinary N deposition and thus N leaching (Stout *et al.* 2001; AgFirst 2009). Restriction of N fertiliser application can reduce N inputs to dairy farms, which reduces stocking rate due to decreases in pasture production (AgFirst 2009). Nitrification inhibitors are chemicals applied to pasture that retard the conversion of ammonium to nitrate through impeding the activity of nitrifying bacteria (Monaghan *et al.* 2007a,b). Dicyandiamide (DCD) application is costly, but can reduce abatement cost through decreasing leaching without concomitant reduction in productive inputs, such as cow number and nitrogen fertiliser (Doole and Paragahawewa 2011). More broad-based restriction of nitrogen inputs to dairy farms can be effective, but requires detailed recording of farm management activities (Lally *et al.* 2009). Restriction of the estimated level of N leaching on a farm considers the multiple factors driving such emissions from dairy farms (Groeneveld *et al.* 1998), although this requires the development of a robust metric to evaluate leaching loads for individual farms. With the measurement of N leaching, there is also the possibility to trade emissions entitlements among heterogeneous dairy farms (Doole and Pannell 2012).

The objective of this study is to evaluate a set of policies for reducing N leaching on Waikato dairy farms, while accounting for climatic variability and soil heterogeneity. This is valuable to inform the design of sound regulatory policies in the main dairy farming region of New Zealand, but also internationally given that nonpoint emissions from pastoral agriculture are a primary cause of declining water quality worldwide (United Nations Environmental Program (UNEP) 2012). The incorporation of both climate variability and soil heterogeneity promotes the broad value of this analysis, given the dearth of studies that include these elements (see Kampas and White 2004, for an exception).

A stylised, conceptual model is used to evaluate several policies drawn from the authority responsible for water quality management in the study region. Abstract, conceptual models have been used for many years to gain insight into general principles for resource (Clark 2010) and environmental management (Dasgupta 1982). In contrast, empirical models have primarily been applied to analyse management within a specific context at a greater degree of detail. The rapid development of powerful computing resources has stimulated interest in the use of numerical methods to construct detailed, yet stylised, models of different systems (Judd 1998). The use of numerical methods greatly increases the amount of detail that can be considered in a conceptual model. However, the key limitation is that the general applicability of the conceptual model is restricted by the case study used to parameterise the model. For this reason, the value of a stylised, numerical approach stems mainly from its capacity to represent a rich description of the important processes within a given case study in a transparent, yet meaningful, way.

Policies evaluated in this study are restrictions placed on N fertiliser, stocking rate, N fertiliser and stocking rate together, and N leaching level. The analysis considers the inherent variability of N leaching and ambient N loads. Stochasticity is an important feature of nonpoint pollution (Kampas and White 2004), but one that has not been studied previously with regard to N leaching from NZ dairy farms. Nevertheless, policy targets are based on deterministic, measured outcomes. This is consistent with current approaches to nonpoint pollution management in NZ, such as within the Taupo catchment where N leaching is estimated using the OVERSEER software (Wheeler *et al.* 2006).

2. Model

This section describes the bioeconomic model used to assess the relative cost of alternative nonpoint pollution policies. The nonlinear optimisation model (Bazaraa *et al.* 2006) incorporates five correlated, stochastic processes that describe important biophysical attributes of the problem. Their inclusion precludes the use of analytical methods.

2.1. Farm management

Assume a catchment involves two farmers (i = {1,2}).The model represents a single year to highlight key concepts. Each farm has a different soil type, with N leaching risk differing between them.

The input decisions of each farmer affect the N level of a waterway. Three inputs are defined. The decision variable S^i represents stocking rate (cows/ha) on farm *i*. This increases production, but increases N leaching. The decision variable F^i represents the level of N fertiliser (kg/ha) applied by farmer *i*. This increases production, but increases N leaching. The inhibitor is applied in a separate application to nitrogen fertiliser and at a constant rate across the area of the farm on which it is used. The area of the farm over which the inhibitor is applied can vary according to the need for reducing nitrification. Thus, the decision variable D^i represents the proportion of the farm on which nitrification inhibitors (i.e. dicyandiamide or DCD) are applied. The first two variables represent key production decisions, while the last is a mitigation strategy.

Several variables describe farm output, as an explicit function of these decision variables. These decision variables are related to farm output through statistical metamodels, defined below in Equations 1–4. A statistical metamodel is a response surface that has been estimated from output from a larger model using linear or nonlinear regression (Kleijnen 2008). Here, the metamodels are fitted to the results generated from a large number of runs of a farm-level model (Section 2.3). Metamodelling is valuable to reduce model complexity and size (Kleijnen 2008). Metamodels fit through regression methods contain omitted variable bias by construction, but this is compensated for by the subsequent simplification of the model containing the metamodel relationship and through the high quality fits generally obtained in the regression (e.g. Table 1) (Friedman 1996; Kleijnen 2008).

The primary use of metamodelling is to describe the relationship between a subset of variables from a larger simulation model, rather than describe the relationship between the output variable and the primary contextual drivers of a given dependent variable in reality (Friedman 1996; Kleijnen 2008). Thus, it is recommended scientific practice to define a metamodel over all treatments and exclude others not considered in the experiment (Friedman 1996; Kleijnen 2008). This is consistent with standard practice in the statistical analysis of agricultural experiments (Gomez and Gomez 1984). Thus, only decision variables are defined as regressors within the equations defined below. Input variables that have no effect on the dependent variable are found to be statistically insignificant. This approach is standard practice where output from a farm-level model is used to develop a more stylised framework (e.g. Segarra and Taylor 1987; Doole and Pannell 2012).

Metamodels to reflect profit, lactation length, milk production and maize silage use are fitted through linear equations, where β^i represents the coefficients for farmer *i*.

Output variable P^i represents farm profit (\$/ha). This is computed:

$$P^i = \beta^i_{aa1} + \beta^i_{aa2}S^i + \beta^i_{aa3}(S^i)^2 + \beta^i_{aa4}F^i + \beta^i_{aa5}(F^i)^2 - \beta^i_{aa6}D^i. \tag{1}$$

There is a quadratic relationship between farm profit and stocking rate and also between farm profit and N fertiliser application. These relationships are concave, with profit increasing with intensification on the left-hand side of the highest points of the quadratic relationships, but declining past these optimal points. The decline occurs with an increasing stocking rate because the benefits of a higher stocking rate for production and promoting pasture utilisation become dominated by the negative impacts of low per-cow production and need for costly supplement (MacDonald *et al.* 2011). The decline occurs with an increasing fertiliser application rate because the additional pasture growth becomes of inadequate value to the farm, relative to the fertiliser cost required to achieve it (e.g. Makowski and Wallach 2002). The curvature of each of these relationships is consistent with the concave relationship between input use and profit in microeconomic theory (Jehle and Reny 2011). Nevertheless, the sensitivity of model output to different relationships is explicitly tested (Section 3.5).

Equation 1 is set to be equivalent across farms to focus on the implications of soil heterogeneity for N leaching. The key driver for variation in profit on heterogeneous soil types on NZ dairy farms, for a given management strategy, is differences in pasture growth (Savage and Lewis 2005). There is scarce information pertaining to the relative growth of pasture on these specific soils. However, there is substantial evidence that they are similar. First, these are both allophanic soils present in the same catchment and climate. Thus, anecdotal evidence suggests that the distributions of pasture production on both soils will have many common values in reality (Iris Vogeler, pers. comm.). Second, this is supported by the distributions of pasture production estimated for 129 farms for Soil 1 and for 158 farms for Soil 2 by Doole and Pannell (2012). The high degree of commonality between the distributions of pasture production on both soil types motivates the use of the same profit function on both soils, given the importance of pasture growth in the determination of farm profit.

Output variable L^i represents mean lactation length (days/cow). This is computed:

$$L^i = \beta^i_{b1} + \beta^i_{b2}S^i + \beta^i_{b3}F^i + \beta^i_{b4}D^i. \tag{2}$$

Output variable M^i represents milk production (kg MS/ha).[1] This is computed:

[1] MS denotes milk solids, the proportion of milk that consists of fat and protein. This is the standard measure of milk production in New Zealand.

$$M^i = \beta^i_{c1} + \beta^i_{c2}S^i + \beta^i_{c3}F^i + \beta^i_{c4}D^i. \quad (3)$$

Milk production per cow is reported in Tables 3–6. This is computed through division of milk produced per ha (Eqn 3) on a given farm divided by the stocking rate (represented by variable S) on this farm.

Output variable Z^i represents maize silage use (t/ha), the primary imported supplement used on Waikato dairy farms. Use of supplements is an important strategy to support higher production from pasture-based NZ dairy farms (Clark *et al.* 2007). This is computed:

$$Z^i = \beta^i_{d1} + \beta^i_{d2}S^i + \beta^i_{d3}F^i + \beta^i_{d4}D^i. \quad (4)$$

The functional forms of Equations 1–4 are selected based on the stylised facts of the process involved, simplicity and clarity, and the level of fit obtained. Sensitivity analysis regarding alternative formulations is important. Equation 1 is a key equation in the model, as it determines the level of profit used in the objective function. In contrast, Equations 2–4 are simple linear relationships that report important output as a function of the key decision variables, but which do not influence the abatement cost dynamics central to model output. Thus, sensitivity analysis is focused on the impacts of different formulations of Equation 1.

The first alternative formulation of the profit function is the linear relationship:

$$P^i = \beta^i_{ab1} + \beta^i_{ab2}S^i + \beta^i_{ab3}F^i + \beta^i_{ab4}D^i. \quad (5)$$

This is the simplest perceivable formulation of the profit function.

The second alternative formulation of the profit function is the logarithmic relationship:

$$P^i = \beta^i_{ac1} + \beta^i_{ac2}S^i + \beta^i_{ac3}\ln(S^i) + \beta^i_{ac4}F^i + \beta^i_{ac5}\ln(F^i) - \beta^i_{ac6}D^i. \quad (6)$$

This formulation is employed since, like Equation 1, it captures declining marginal profitability of the stock and fertiliser inputs. However, profit does not decline at high levels of the stock and fertiliser inputs, unlike in the quadratic formulation in Equation 1. A logarithmic transformation is not considered for D^i in Equation 6, as this variable contains some zero values.

2.2. Water quality

Nitrate leaching is represented as a log-normally distributed random variable since it is non-negative, and this distribution is consistent with theory (Addiscott 1996) and modelling studies (Vogeler *et al.* 2011).

A given level of nitrate leaching NB^i (kg N/ha) occurs on farm i, regardless of input decisions. This background (or native) level of leaching is described as follows:

$$NB^i = \epsilon^i_{NB}, \tag{7}$$

Where ϵ^i_{NB} is a log-normally distributed random variable that varies with climate, rainfall and drainage conditions.

Also, management decisions affect nitrate leaching NM^i (kg N/ha) from farm i. NM^i is log-normally distributed. If ϖ is a random variable with a normal distribution, then $\exp\varpi$ has a log-normal distribution (Greene 2012). Accordingly, NM^i is computed as follows:

$$NM^i = \exp(\beta^i_{g^i_1} + \beta^i_{g^i_2} S^i + \beta^i_{g^i_3} F^i + \beta^i_{g^i_4} D^i + \epsilon^i_{NM}) \tag{8}$$

where the coefficients $\beta^i_{g^i_1} - \beta^i_{g^i_4}$ are estimated through linear regression and ϵ^i_{NM} is a normally distributed random variable that varies with climate, rainfall and drainage conditions.

Total nitrate leaching on each farm N^i (kg N/ha) is computed as follows:

$$N^i = NB^i + NM^i. \tag{9}$$

Total N leaching N^i itself is a log-normally distributed random variable, as it is the sum of two random variables with log-normal distributions.

Nitrate leached from dairy land enters a hypothetical lake. A given load of nitrogen is present in the waterway WB (kg N), regardless of management on dairy land. This background load represents leaching from other land uses in the catchment (e.g. urban run-off, forest, and sheep and beef farms). It is assumed that the ratio of nondairy land to dairy land (b) is equivalent to that reported for the Waikato catchment in Alexander *et al*. (2002).

The background load WB (kg N) in the hypothetical lake is defined as follows:

$$WB = \epsilon_{WB} b \sum_{i=1}^{2} h^i \tag{10}$$

where ε_{WB} is a lognormally distributed random variable denoting background N level (kg N/ha) and h^i is the size of farm i (ha). The shape of this distribution is based on the non-negativity of N loadings and extensive empirical evidence (e.g. Smith *et al*. 2003).

The total N load reaching the waterway WM^i (kg N) from farm i is as follows:

$$WM^i = (1 - a^i) h^i Ni, \tag{11}$$

where a^i is an attenuation factor. Attenuation is the proportional loss of nitrogen between leaching and measurement in the lake due to denitrification, N immobilisation and sedimentation. The variables WM^i are lognormally distributed, as they represent the sum of a number of log-normally distributed random variables.

The total N load in the waterway W (t N) is thus the following:

$$W = \alpha\left[WB + \sum_{i=1}^{2} WM^{i}\right], \tag{12}$$

where α = 0.001 is a multiplier that converts the quantities from kilograms to tonnes.

Water quality may be described in terms of the median concentrations of total nitrogen (TN) and total nitrate (TI) in the waterway. TN is computed from the ambient load (W) through the relationship $TN = \eta W$, where η is a multiplier. TI is computed from TN through the relationship $TI = \kappa TN$, where κ is a multiplier. Coefficients η and κ are computed for a large number of catchments in the Waikato region using a hydrological model. The coefficients for a randomly selected catchment are used to generate TN and TI levels, given that a hypothetical catchment is studied. The relevant values are η = 0.0061 and κ = 0.8927.

2.3. Model data

The Integrated Dairy Enterprise Analysis (IDEA) model (Doole *et al.* 2013) is a farm-level model that provides a comprehensive description of a pasture-based dairy farm in New Zealand. It identifies the farm plan that optimises annual profit using nonlinear programming (Bazaraa *et al.* 2006). The model incorporates several important processes not considered in previous models. New Zealand dairy pastures are typically rested for periods (30–100 days) between grazing events. IDEA includes an explicit relationship between the duration of resting, postgrazing residual herbage mass, rate of herbage accumulation and digestibility of herbage. Cows can be fed below potential intake to help match feed supply and feed demand better. In IDEA, the level of pasture utilisation is also a curvilinear function of stocking rate, as discussed by Doole *et al.* (2013).

IDEA is used to generate profit, lactation length, milk production, maize silage use and urinary load for alternative combinations of stocking rate, nitrogen fertiliser application and DCD use. A full factorial of the following sets were defined: stocking rates of [2,2.5,…,4.5] cows/ha, N fertiliser application rates of [50,150,…,300] kg/ha and DCD applied on [0,25, …,100] per cent of the farm. Broader sets were initially defined, but rendered infeasible combinations. For example, a stocking rate of 5 cows could not be sustained with any level of N fertiliser application on the pasture-based farm, due to intake constraints related to the potential onset of acidosis with high levels of maize silage consumption (Kolver *et al.* 2001).

Equations 1–4 are defined as statistical metamodels of IDEA output. Metamodels are estimated in this analysis using the SHAZAM econometrics software (Whistler *et al.* 2010). Table 1 reports the results of the estimated metamodels for farm management variables. Each is characterised by a high level of accuracy (Table 1), as measured by adjusted R^2, with the estimated model for lactation length being the least accurate, but still accounting for 75 per cent of the variation. There is a negative relationship between maize silage feeding and nitrogen fertiliser application in Table 1. This is expected, as both practices have an ability to increase the total supply of energy available to the cow herd on a New Zealand dairy farm. The profit functions defined in Equations 5 and 6 are listed in the final two rows of Table 1. It is evident that they do not fit the data as well as the function used in the baseline, according to the adjusted R^2 level. Moreover, the coefficients for livestock density in Equation 5 and nitrogen fertiliser in Equation 6 are not statistically significant at the 5 per cent level in the alternative formulations.

Nitrification inhibitors may promote pasture production through improving N retention in the soil (Doole and Paragahawewa 2011). However, no additional pasture growth is considered with their application in this study. This follows experimental results that reveal its inability to improve pasture production under practical conditions on New Zealand dairy farms. MacDonald *et al.* (2010) observed no pasture response following DCD application under practical farming conditions. Moreover, the Nitrous Oxide Mitigation Research programme, run throughout New Zealand from 2009 to 2012, showed the average increase in pasture production to be in the order of 3 per cent, but differences were only statistically significant in a third of the trials (Pastoral Greenhouse Gas Research Consortium (PGGRC) 2012). As a result of this assumption, estimated coefficients for DCD have a low statistical significance in the regressions for lactation length (β_{b4}), milk production (β_{c4}) and maize silage use (β_{d4}).

The N leaching data used in Equations 7 and 8 are generated using the Agricultural Production Simulator (APSIM). APSIM is a simulation model that provides a modelling framework for the synthesis of different models of the processes involved in a given agronomic system (Snow *et al.* 2011). The relationship between input decisions (stocking rate, N fertiliser application and DCD use) and nitrate leaching on two soils is generated from APSIM output. Soil type 1 (S1) is a Oropi sand – a Buried Allophanic Orthic Pumice soil (Hewitt 1998). Soil type 2 (S2) is a Horotiu silt loam – a Typic Orthic Allophanic soil (Hewitt 1998). The definition of different soil types provides insight into the cost-effectiveness of alternative policies under soil heterogeneity.

Levels of nitrate leaching for a urinary load at the urine patch level of 400 kg/ha are simulated for the period 1973–2006, using daily weather data from the NIWA Virtual Climate Station data set (Tait and Turner 2005). The background level of N leaching on each soil type (Eqn 5) is computed using MATLAB (Table 2). The fraction of the urinary N load leached in each month in each year is computed from APSIM output. The APSIM model is not used to generate urinary load for each model run. Rather, IDEA computes the urinary N load excreted in each fortnight for a broad range of alternative combinations of stocking rate, N fertiliser application and DCD use (see above). The fortnightly IDEA output is multiplied by the fractions computed for the respective fortnights using APSIM. This yields a distribution of the N leaching arising from the urinary N deposited in each fortnight, based on the annual variability computed in APSIM. The aggregation of these fortnightly distributions yields an annual distribution of N leaching for a given input combination.

These data are used to estimate Equation 8 for each soil type using SHAZAM. Nitrate leaching is log-normally distributed. Thus, ordinary least squares (Greene 2012) are used to estimate a log-linear relationship between In NM_i and the explanatory variables, S^i F^i and D^i. Results are reported in Table 2. The high annual variability of N leaching reduces the accuracy of the regression, with R^2 = 0.012 for Soil 1 and R^2 = 0.11 for Soil 2. The coefficient estimated for nitrogen fertiliser ($\beta^i_{g^i_3}$) is not statistically significant at the 5 per cent level for both soil types (Table 2). This result is in line with expectations. The primary N losses from a New Zealand dairy farming system are associated with high levels of N deposited in urine patches by cows grazing high-protein pastures. Indeed, around 95 per cent of leached N comes from urine patches, while only 4 per cent comes from nitrogen fertiliser and 1 per cent comes from effluent (de Klein *et al.* 2010).

The background load of N in the waterway (kg N/ha) (Eqn 10) is drawn from data for the Waikato River in Alexander *et al.* (2002).

Table 1 Parameter estimates for each metamodel of the output variables describing farm management

Output variable	Unit		Coefficient (β) 1	2	3	4	5	6	Adj. R^2
Profit (P^i)	\$/ha	aa	−1565.7 (0.000)	1792 (0.000)	−276.74 (0.000)	3.67 (0.000)	−0.0062 (0.005)	−216.15 (0.002)	0.85
Lactation length (L^i)	days /cow	b	300.21 (0.000)	−6.48 (0.000)	−0.0084 (0.08)	−1.05 (0.86)	–	–	0.75
Milk prod. (M^i)	kg MS /ha	c	383.84 (0.000)	222 (0.000)	−0.0331 (0.13)	−1.58 (0.89)	–	–	0.99
Maize silage (Z^i)	t/ha	d	−4.4 (0.000)	2.46 (0.000)	−0.0055 (0.000)	−0.049 (0.88)	–	–	0.98
Profit (P^i)	\$/ha	ab	1373.5 (0.000)	−32.81 (0.203)	1.575 (0.000)	−196.82 (0.198)	–	–	0.73
Profit (P^i)	\$/ha	ac	1753.4 (0.000)	−1555 (0.000)	4763.1 (0.000)	−295.23 (0.736)	289.37 (0.048)	−211.21 (0.009)	0.83

P-values for regression coefficients are stated in brackets alongside each estimate.

2.4 Policy simulation

The nonlinear optimisation model is constructed in the General Algebraic Modelling System (GAMS) (Brooke *et al.* 2012). It is solved using the global optimisation solver BARON given the nonconvexity of the model and the susceptibility of gradient algorithms to the identification of local optima (Bazaraa *et al.* 2006). The optimisation model identifies the solution that maximises total profit ($J = \sum_{i=1}^{2} P^i$) for a given policy instance.

Details of the base solution are discussed in Section 3.1.

The implications of four policies for reducing N leaching by 10 and 20 per cent are explored in Sections 3.2 and 3.3, respectively. These policies are drawn from discussions with the Waikato Regional Council, the regulatory body charged with sustaining water quality in the study region. The policies are as follows:

1. No N fertiliser application is permitted. This restricts a key input that supports higher stocking rates. This is referred to as the 'NF limit' policy.
2. Stocking rate is limited. This can reduce urine deposition through decreasing livestock intensity. This is referred to as the 'SR limit' policy.
3. No N fertiliser application is permitted and stocking rate is limited. This policy recognises that multiple inputs may have to be targeted due to imperfect correlation between N leaching and a single input. This is referred to as the 'SR + NF limit' policy.
4. Mean N leaching is limited. Mean leaching can be estimated using an appropriate biophysical model, such as OVERSEER (Wheeler *et al.* 2006). This is referred to as the 'NL limit' policy.

Policies are simulated through the introduction of constraints on the regulated quantity. The degree to which inputs must be reduced to attain a given reduction in N leaching is identified through iterative means. Input-based policies targeting imported supplement are deemed too complex from an administrative standpoint given the high number of feedstocks available to farmers. Indeed, Clark *et al.* (2007) highlighted that more than 30 types of supplementary feed are available to NZ dairy farmers.

The variability of water quality attributes in response to environmental policy is discussed in Section 3.4. Stochastic effects are incorporated using appropriate random number generation procedures in GAMS (Brooke *et al.* 2012). One thousand draws are generated for each random variable. The policies simulated in the model are based on mean amounts, so stochastic quantities representing variability in water quality are not restricted. Thus, stochastic programming (Shapiro *et al.* 2009) is not needed, as probabilistic processes do not enter the objective function and/or define the feasible region for optimisation.

Section 3.5 explores the sensitivity of the model to different specifications of the profit function. The profit functions defined in Equations 1, 5 and 6 are

Table 2 Parameter estimates for each metamodel of the output variables describing water quality

Output variable	Unit		Coefficient (β)				ε	Adj. R^2
			1	2	3	4		
Native leaching for Soil 1 (NB^i)	kg N/ha	–	–	–	–	–	L(1.17,1.89)	–
Native leaching for Soil 2 (NB^2)	kg N/ha	–	–	–	–	–	L(0,93,1.92)	–
N leaching for Soil 1 (NM^1)	Ln(kg N/ha)	g^1	2.83 (0.000)	0.21 (0.000)	0.00019 (0.38)	−0.15 (0.000)	N(0,0.59)	0.12
N leaching for Soil 2 (NM^2)	Ln(kg N/ha)	g^2	2.64 (0.000)	0.22 (0.000)	0.00024 (0.21)	−0.13 (0.000)	N(0,0.6)	0.11
Native level of N in waterway (WB)	kg N/ha	–	–	–	–	–	L(1.12,0.57)	–

P-values for regression coefficients are stated in brackets alongside each estimate.

each tested, with the implementation of a 20 per cent reduction in N leaching. This scenario is selected because it is the most cost-effective means of achieving the largest simulated decrease in leaching.

3. Results and discussion

3.1. Base results

Base model output is reported in Table 3. The model provides a reasonable description of management on a standard farm in the Waikato region of New Zealand. Stocking rate is within 5 per cent of that drawn from survey data (DairyNZ 2011), while results for milk production per cow and lactation length are within 1 and 2 per cent, respectively, of these data. Moreover, milk production per cow is within 2 per cent of mean production from an independent sample of 410 Waikato dairy farms (Doole and Pannell 2012). Imported supplement (maize silage) makes up around 12 per cent of total feed intake (data not shown). This is consistent with the production intensity of an average farm in the Waikato region, which imports between 10 and 20 per cent of feed annually. DCD is not required in the base model, as mitigation is not necessary.

The Oropi sand (S1) has a leaching rate of 33 kg N/ha, which is around 23 per cent lower than that of the Horotiu silt loam (S2). This is consistent with the trend observed in the modelling study of Snow *et al.* (2011). This highlights that a meaningful representation of soil heterogeneity is present in the model. The lower N leaching intensity (kg N leached per kg MS) (0.03) on S1 is consistent with a farm with low N leaching generally, while the higher intensity rate (0.039) on S2 is consistent with an average Waikato dairy farm (AgFirst 2009). Moreover, kg N leached per cow is higher on S2 given its higher leaching rate than S1 at an equivalent stocking rate.

3.2. Achieving a 10 per cent reduction in N leaching

Models results for achieving a 10 per cent reduction are reported in Table 4. The NF scenarios fail to achieve a 10 per cent reduction in N leaching, with N leaching declining by only 4 and 6 per cent on S1 and S2, respectively. Thus, this output is not reported in Table 4. This limited response arises due to an 82 per cent increase in imported supplement use, which allows stocking rates to remain the same as in the base model. This indicates several factors. First, N fertiliser and imported supplement are substitutes when either one is unavailable, given their individual ability to increase the total supply of energy available on a pasture-based NZ dairy farm. The presence of this substitution can offset the value of N fertiliser restrictions for reducing N leaching. Second, the restriction of N fertiliser application is ineffective in reducing leaching, as N fertiliser is generally applied according to best practice in the NZ dairy industry and thus has a minimal direct impact on N

Table 3 Key model output for baseline solution

Variable	Unit	Output
Profit	$/ha	1879
Stocking rate	cows/ha	3.24
Milk production per cow	kg MS/cow	337
Milk production per ha	kg MS/ha	1093
N fertiliser	kg N/ha	136
Maize silage	t/ha	1.96
Lactation length	days	277
N leaching	kg N/ha	S1 = 33, S2 = 43
N leaching intensity	kg N/kg MS	S1 = 0.03, S2 = 0.039
DCD	Prop. of area	0
N load in lake	t N	95.57

Soil type 1 (S1) is the Oripi sand, while Soil type 2 (S2) is the Horotiu silt loam.

leaching (Monaghan *et al.* 2007a; de Klein *et al.* 2010). Rather, N fertiliser contributes indirectly through increasing pasture production and hence stocking rate and urine deposition.

Table 4 presents model output for those policies capable of attaining a 10 per cent decrease in leaching.

Stocking rate is reduced by around 17 per cent on both soils to reduce urinary N deposition sufficiently to meet the N leaching target. Maize silage use decreases by 70 per cent, given the reduced demand from stock. Milk production per cow increases by 7 per cent to help offset the cost of the stocking rate reduction (Table 4). However, profit falls by 5 per cent on both soils due to a reduction in milk produced per ha by 11 per cent. N fertiliser application is equivalent to that in the base model, as it is a cost-effective means of promoting milk production (Table 4). This demonstrates the potential threat posed by the increased use of unrestricted inputs when other inputs are constrained in nonpoint pollution policy (Stout *et al.* 2001). This is similar to the capital-stuffing problem encountered in fisheries, whereby fishers increase capital investment in gear when boat numbers are restricted (Clark 2010).

Extending stocking rate restrictions to incorporate a ban on N fertiliser application offsets the need for large decreases in livestock density. Indeed, stocking rate falls by only 4 and 14 per cent on S1 and S2 (Table 4), respectively, compared with 17 per cent for the 'NF limit' scenario. Also, milk production only falls by 3 and 6 per cent on S1 and S2, respectively. Nevertheless, the lack of N fertiliser promotes the importation of supplement, with maize silage use increasing by 58 and 42 per cent on S1 and S2, respectively. This is less profitable, with profit falling around 30 per cent on both soils, as the substitution of N fertiliser with maize silage increases input costs.

Targeting estimated N leaching is the most cost-effective method to restrict N leaching by 10 per cent. Profit decreases by only 4 per cent on both soils, compared with 5 per cent on both soils with the 'SR limit' policy and 30 per cent on both soils with the 'SR+NF limit' policy. Stocking rate is reduced by around 17 per cent, but milk production per ha decreases by only 10 per cent

Table 4 Key model output associated with restrictions to stocking rate (SR limit), nitrogen fertiliser and stocking rate (NF+SR limit) combined, and nitrate leaching (NL limit) to achieve a 10 per cent decrease in N leaching

Variable	Unit	Policy instrument						
		Base	SR limit (S1)	SR limit (S2)	NF+SR limit (S1)	NF+SR limit (S2)	NL limit (S1)	NL limit (S2)
Profit	$/ha	1879	1793	1793	1325	1307	1806	1800
Stocking rate	cows/ha	3.24	2.68	2.68	3.04	2.91	2.74	2.71
Milk prod. per cow	kg MS/cow	337	362	362	349	354	358	360
Milk prod. per ha	kg MS/ha	1093	969	969	1060	1031	982	976
N fertiliser	kg N/ha	136	136	136	–	–	125	128
Maize silage	t/ha	1.96	0.59	0.59	3.1	2.78	0.86	0.76
Lactation length	days	277	280	280	280	281	280	280
N leaching	kg N/ha	S1 = 33, S2 = 43	29	39	29	39	29	39
N leaching intensity	kg N/kg MS	S1 = 0.03, S2 = 0.039	0.03	0.04	0.028	0.037	0.03	0.04
DCD	prop. of area	0	0	0	0	0	0	0

The level of simulated restriction is fixed for each soil type.

as milk production per cow increases (Table 4). High rates of N fertiliser (around 125 kg N/ha) are still applied, along with a moderate amount of maize silage (around 0.8 t/ha).

3.3. Achieving a 20 per cent reduction in N leaching

Table 5 presents model output for those policies capable of attaining a 20 per cent decrease in leaching.

Stocking rates are reduced by around 30 per cent on both soils within the 'SR limit' policy to meet the more stringent leaching reduction. No maize silage is required given this reduction. However, milk production is increased by around 15 per cent per cow, partly due to an extended lactation (Table 5). Profit decreases by 19 and 21 per cent on S1 and S2, respectively, as milk production per ha decreases by around the same amount. N fertiliser application remains above 83 kg N/ha, as it remains a cost-effective tool to support greater milk production.

Stocking rates are reduced by around 25 per cent when the 'NF+SR limit' policy is used to reduce N leaching by 20 per cent. Milk production per cow increases by more than 12 per cent, but profit still decreases by around 40 per cent on both soils, as maize silage is used instead of N fertiliser but is a more expensive source of energy for the cow herd (Table 5).

Restriction of estimated N leaching by 20 per cent is the most cost-effective policy. Profit falls by 18 and 16 per cent on S1 and S2, respectively, with milk production per ha decreasing by more than 13 per cent (Table 5). These reductions in profit are less than those identified for the other policies, with profit falling by around 20 per cent for the 'SR limit' policy and around 40 per cent with the 'NF+SR limit' policy. Nevertheless, milk production per cow is increased by around 10 per cent to offset the costs imposed on the farm due to the introduction of these regulations. The cost-effective combination of N fertiliser application and use of maize silage is retained in the 'NL limit' scenario. Indeed, N fertiliser application is only altered by a maximum of 4 kg N/ha.

A key strategy used to reduce N leaching is the application of DCD on around 75 per cent of each soil type (Table 5). DCD prevents nitrate leaching through preventing the nitrification of ammonium deposited on the soil by cow urine. The 'SR limit' and 'NF+SR limit' policies involve constraints on stocking rate and nitrogen fertiliser, which reduce urine deposition but ignore the fate of urinary N once it is excreted. Indeed, there is no economic incentive accruing to the use of DCD within these scenarios, as it cannot help to offset required reductions in either input. In contrast, the potential use of N inhibitors allows the explicit consideration of mitigations at each stage of the N cycle. The 'NL limit' policy involves constraints levied directly on N leaching, which is directly affected by DCD use (Monaghan *et al.* 2007a,b). Thus, the economic value of DCD is promoted within this scenario, through a shadow price associated with its capacity to retard the rate of N leaching.

Table 5 Key model output associated with restrictions to stocking rate (SR limit), nitrogen fertiliser and stocking rate (NF+SR limit) combined, and nitrate leaching (NL limit) to achieve a 20 per cent decrease in N leaching

Variable	Unit	Policy instrument						
		Base	SR limit (S1)	SR limit (S2)	NF+SR limit (S1)	NF+SR limit (S2)	NL limit (S1)	NL limit (S2)
Profit	$/ha	1879	1528	1489	1154	1100	1594	1570
Stocking rate	cows/ha	3.24	2.22	2.19	2.43	2.32	2.57	2.54
Milk prod. per cow	kg MS/cow	337	392	394	380	387	368	369
Milk prod. per ha	kg MS/ha	1093	870	863	923	898	945	936
N fertiliser	kg N/ha	136	90	83	-	-	121	125
Maize silage	t/ha	1.96	0	0	1.58	1.3	0.46	0.32
Lactation length	days	277	284	285	284	285	281	281
N leaching	kg N/ha	S1 = 33, S2 = 43	26	34	26	34	26	34
N leaching intensity	kg N/kg MS	S1 = 0.03, S2 = 0.039	0.03	0.04	0.028	0.038	0.028	0.037
DCD	prop. of area	0	0	0	0	0	0.73	0.78

The level of simulated restriction is fixed for each soil type.

3.4. Water quality implications

N leaching is highly variable and log-normally distributed on both soils (Figure 1). The distributions for N leaching on both soils have long right-hand tails in the absence of regulation, but especially that for the silt loam soil (S2) (Figure 1, Soil 2). These tails decrease in length with regulation. For example, the maximum level of N leaching on S1 with the 20 per cent regulation (Figure 1c, Soil 1) is more than 10 kg N/ha lower than that without regulation (Figure 1a, Soil 1). Additionally, the maximum level of N leaching on S2 with the 20 per cent regulation (Figure 1c, Soil 2) is more than 15 kg N/ha lower than that without regulation (Figure 1a, Soil 2). Overall, model output shows that standard policy responses to N leaching on NZ dairy farms will do little to arrest substantial variability in N leaching.

A reduction in mean leaching on either soil type by 1 kg N/ha, for any level of N reduction less than 20 per cent of the baseline load, reduces the mean ambient N load by 2.75 t. The response in mean ambient load is a 3 per cent change, while a 1 kg N/ha change on S1 and S2 represents a 3 and 2 per cent change in mean baseline load, respectively. Accordingly, the response between a reduction in mean load and an improvement in mean water quality is almost directly proportional. So, small changes in loadings at the farm level do not achieve large improvements in water quality at the catchment level. Rather, a significant reduction in farm load is required to achieve meaningful improvements at the catchment scale.

However, substantial variability around these averages persists upon regulation. The cumulative distribution of total N load in the waterway (ambient N) signifies the broad variability of water quality without regulation (Figure 2). Moreover, this variability changes little with regulation, with the cumulative distribution moving leftwards, but only slightly, as limits on N leaching become more restrictive. These results indicate that inherent volatility in water quality, mainly due to climate variability, can mask the benefits of regulatory action at farm level in any given year. Indeed, the minimum and maximum levels of ambient N differ by more than a factor of four for each scenario. This range is very consistent with N levels measured in waterways elsewhere in New Zealand (Monaghan *et al.* 2007b).

The baseline median concentrations of *TN* and *TI* in the model are 0.59 g/m^3 and 0.53 g/m^3, respectively. The total nitrate concentration (*TI*) is well below the upper threshold required for water to be of a fair quality (6.9 g/m^3) (Hickey 2013). However, the computed level of *TN* is above that considered satisfactory by the Waikato Regional Council (0.5 g/m^3) (Environment Waikato 2008). Restriction of N leaching by 10 per cent yields concentrations of *TN* and *TI* in the model as 0.54 g/m^3 and 0.48 g/m^3, respectively. In comparison, restriction of N leaching by 20 per cent yields concentrations of *TN* and *TI* in the model as 0.49 g/m^3 and 0.43 g/m^3, respectively. Total nitrate concentration stays below 1 g/m^3 across all scenarios, which signifies excellence in the framework of Hickey (2013). However, a 20 per cent

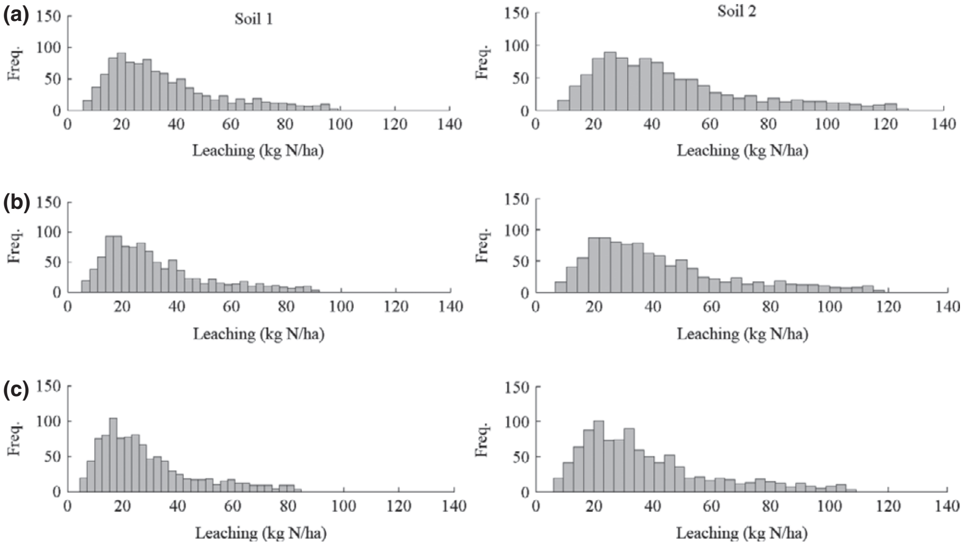

Figure 1 Distribution of N leaching in the (a) base model, (b) with a 10 per cent restriction on N leaching and (c) with a 20 per cent restriction on N leaching

reduction in N leaching load is required for the median *TN* concentration to achieve an acceptable level.

3.5. Sensitivity analysis

Profit is significantly affected with alternative specifications of the profit function, especially for the logarithmic function (Table 6). This is intuitive, as the alternative formulations are broadly divergent. The core management plan is robust to changes in the specification of the profit function. Stocking rate and milk production are both robust, with maximum changes of 3–4 per cent relative to the baseline profit function (Table 6). Lactation length and N leaching levels show no marked change. Nevertheless, the optimal strategies that support this core strategy vary. Nitrogen fertiliser use is higher than the baseline with the linear specification, but zero in the logarithmic specification. In contrast, maize silage is zero in the linear specification, but higher than the baseline with the logarithmic specification. This portrays the substitutability of these inputs as a source of additional energy, highlighted above. Additionally, DCD use is higher than the baseline with the linear specification and very low with the logarithmic formulation. The sensitivity analysis highlights that the core insights from the model remain robust to broadly divergent specifications of the profit function, a major change in a model of this kind. Nevertheless, it is important to recognise that the function employed in the main model (Eqn 1) obtains the best fit of all alternatives considered (Table 1).

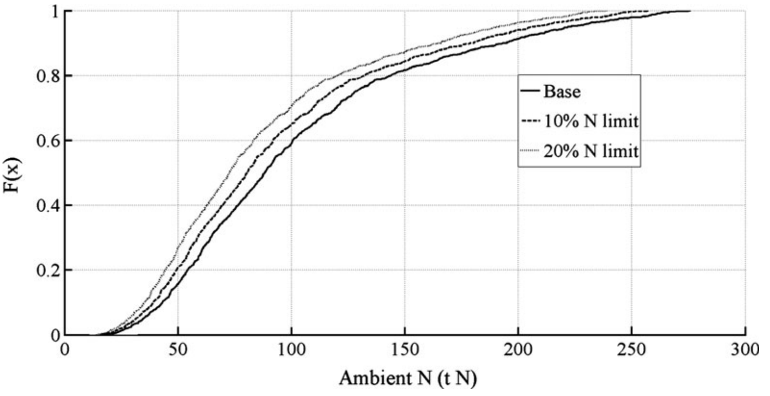

Figure 2 Cumulative distribution of ambient N (t N) in the waterway in the (a) base model, (b) with a 10 per cent restriction on N leaching and (c) with a 20 per cent restriction on N leaching

4. Conclusions

This study presents a comprehensive economic analysis of alternative policies to reduce nonpoint emissions from pastoral agriculture. A nonlinear optimisation model incorporating climate variability and soil heterogeneity is used to explore the implications of different policies, particularly at the farm level. The model is applied within the context of the New Zealand dairy industry, which is responsible for a significant proportion of nonpoint emissions from agriculture in this nation (Doole and Pannell 2012).

Input-based policies suffer from a number of complications. First, within these farming systems, there is invariably a low correlation between the use of a single farm input and N leaching. For example, stocking rate is a key determinant of N leaching, but large stocking rate reductions of 17 and 30 per cent are still required to achieve N leaching reductions of 10 and 20 per cent, respectively, due to the imperfect correlation. This finding can likely be extrapolated to all grazing systems, given the complicated relationship between input use, production and nitrate leaching (de Klein *et al.* 2010). Second, leaching levels may remain high under an input-based policy because of substitution with unrestricted inputs. For example, allowing no use of N fertiliser reduces profit by around 30 per cent, but only decreases leaching by around 5 per cent, as supplement use increases by 80 per cent to sustain stocking rate. This behaviour is expected to hold for grazing systems generally, provided that there is some degree of substitutability between the relevant factors. Third, policies that restrict the use of two inputs are costly. For example, restricting nitrogen fertiliser application and stocking rate reduces profit by 30 and 40 per cent for the 10 and 20 per cent N leaching goals, respectively. This finding also extends to grazing systems in general, as restricting the use of all factors between which substitution can take place limits the degree to which a producer can sidestep regulation. Rather, the

Table 6 Key model output associated with a 20 per cent decrease in N leaching for different versions of the estimated profit function

Variable	Unit	Linear profit function (Eqn 5)		Baseline profit function (Eqn 1)		Log. profit function (Eqn 6)	
		NL limit (S1)	NL limit (S2)	NL limit (S1)	NL limit (S2)	NL limit (S1)	NL limit (S2)
Profit	$/ha	1670	1651	1594	1570	1910	1862
Stocking rate	cows/ha	2.62	2.59	2.57	2.54	2.49	2.46
Milk prod. per cow	kg MS/cow	363	365	368	369	376	378
Milk prod. per ha	kg MS/ha	952	946	945	936	936	930
N fertiliser	kg N/ha	169	164	121	125	0	0
Maize silage	t/ha	0	0	0.46	0.32	1.72	1.64
Lactation length	days	279	279	281	281	284	284
N leaching	kg N/ha	26	34	26	34	26	34
N leaching intensity	kg N/kg MS	0.028	0.036	0.028	0.037	0.028	0.037
DCD	prop. of area	1	1	0.73	0.78	0.1	0.28

farmer must bear the cost of abatement. Last, the use of input-based policies does not motivate the use of mitigation practices targeted at reducing N leaching directly. Indeed, nitrification inhibitors are never used under any input-based policy in this analysis. This has implications for all grazing systems, as it is apparent that input restrictions will never promote the value of mitigation practices that impact leaching loads directly.

Restricting mean N leaching rates directly is a cost-effective option for reducing leaching from NZ dairy farms. A 10 per cent N leaching reduction is achieved at a cost of 4 per cent of profit, compared to 5 per cent of profit with the next most cost-effective strategy. In comparison, a 20 per cent N leaching reduction is achieved at a cost of around 17 per cent of profit, compared to 20 per cent of profit with the next most cost-effective strategy. Its key value above other policies is that it promotes the use of mitigation practices to reduce abatement costs. For example, nitrification inhibitors are used on 75 per cent of the farm area to reduce N leaching when policy seeks to reduce mean N leaching by 20 per cent. However, their cost does not motivate their use under a 10 per cent N leaching restriction. This finding is important more generally, as targeting the pollutant load directly intuitively places a positive value on those mitigation practices that influence its level.

Model output indicates that inherent volatility in water quality, mainly due to climate variability, can mask the benefits of regulatory action in any given year. This highlights the importance of stochastic modelling when evaluating policies to reduce nonpoint pollution. Deterministic frameworks may provide some insight, but this analysis indicates that such models are likely overoptimistic in their predictions. This finding is of general relevance since deterministic models, by definition, cannot represent the variability associated with real biophysical processes. The applied framework also exploits the availability of information regarding the variability of key processes, overcoming the need to coarsely define uncertain variables (e.g. Doole and Pannell 2011). The model differs from those previously employed in economic analysis, as it computes stochastic quantities without including them in the objective function or constraining them. This is consistent with existing environmental policy in New Zealand, but could be extended to include probabilistic constraints (Shapiro *et al.* 2009).

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