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An Inertia Model for the Adoption of New Farming Practices

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Abstract

Nutrient emissions from agricultural land are now widely recognized as one of the key contributors to poor water quality in local lakes, rivers and streams. Nutrient trading has been suggested as a regulatory tool to improve and protect water quality. However, farmers' attitudes suggest that they are resistant to making the changes required under such a scheme.

This paper develops a model of farmers' resistance to change and their adoption of new management practices under nutrient trading regulation. We specify resistance as a bound on the adoption of new practices and allow this bound to relax as farmers' resistance to change weakens.

This paper reflects current work in progress as part of the author's Master's Thesis. Future work will extend and build upon the material presented here. We request that readers refer to this paper only in the absence of a more recent version.

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Key words: agriculture; inertia; mitigation; nutrient trading; technology adoption;

1 Introduction

Nutrient emissions from non-point sources, such as agricultural land, are increasing recognized as one of the key contributors to poor water quality. Declining water quality is a serious problem in many developed countries, including New Zealand, and in an increasing number of developing countries (Sutton et al. 2011, Parliamentary Commissioner for the Environment 2006). Numerical modeling of different approaches to improving water quality can help inform the decisions of both policy makers and local stakeholders. Unfortunately, some simplifying assumptions that are necessary to make numerical modeling tractable reduce the credibility of the associated results.

The NManager model (Anastasiadis et al. 2011) make several simplifying assumptions in order to model the performance of six different designs of nitrogen regulation (including a nitrogen trading scheme) in the Lake Rotorua catchment

(New Zealand). These assumptions include: farmers are willing to change, farmers respond optimally to a nitrogen price, and farmers' decisions are independent of their past decisions and the decisions of other farmers.*

However, evidence suggests these assumptions are a poor representation of reality. Farmers have expressed a reluctance to change where it involves the adoption of unfamiliar farm management practices or technologies (see for example Fenemor et al. 2012); they tend to manage their business with an eight to ten year time horizon; and may have incentives to delay the adoption of new practices or technologies in order to capitalize on learning opportunities (Coleman & Sin 2012). Furthermore, there is a well known psychological phenomenon where people and organizations continue a familiar practice, even though a better one is available, until the cost of continuing with their current practice exceeds the cost of change.

In order to provide a more credible model of farmer behavior, and to reflect the reality identified above, we develop a model of farmers' resistance to change. We describe farmers' resistance to change as their inertia. Farmers' inertia depends on their past behavior, the past behavior of other farmers, and the passing of time. This is a novel and somewhat challenging approach as it involves quantifying something that is difficult to identify and measure.

The paper is set out as follows: In the remainder of this section we review some of the literature relevant to agricultural adoption, and briefly describe the workings of a nutrient trading scheme. In section 2 we specify our inertia model for the adoption of new mitigation technologies and practices. The implementation of the model is discussed in section 3, and section 4 concludes with the future intentions for this work.

1.1 The adoption of new agricultural practices

Research into the factors that affect the adoption on new agricultural practices and technologies have highlighted the importance of networks, information, and costs. Foster & Rosenzweig (1995) find that imperfect knowledge is a key barrier to the adoption of new seed varieties for Indian households, and that households initially learn from their neighbors' experiences. Conley & Udry (2003) draw similar conclusions with respect to the growing of pineapples in Ghana. They find that learning from social networks of other farmers is significant, even after controlling for spatial and serial correlation. Pannell et al. (2006) review the drivers of adoption and the implications to policy makers in Australia. They note that farmers have an excess of information and are almost never passive in their receipt of information.

Meta-analyses of the drivers of adoption have been conducted for the United States. Skinner & Staiger (2005) compare adoption rates of hybrid corn, tractors, and β-blockers (for the treatment of heart attacks) across states. They find that high levels of social and human capital (i.e. involvement in local networks and education) are strongly associated with early adoption, while low financial costs of adoption had a much weaker affect. Skinner & Staiger (2005) also explore the dif-

*We thank audiences at the New Zealand and the Australian Agricultural and Resource Economics conferences (2011 and 2012 respectively) for their honest feedback that these assumptions were too simplistic. Part of the motivation for this paper is in response to their feedback.

ferences between the economic paradigm, where agents are profit or utility maximizers and invest in eduction or new technology only if it will help earn a higher wage; and the sociology paradigm, where eduction, networks and the structure of organizations can empower people to being about change. A more recent study by Baumgart-Getz et al. (2012) emphasizes the importance of farmers' connections to local networks, the quality of their information, and their financial capacity. Farmers' risk aversion was not found to be significant.

A less emphasized determinant of farmers' adoption decisions is farmers' attitudes to farming and to change. Dury et al. (2010) interview farmers in France and identify the following as farmer objectives: maximizing profit or income, establishing and maintaining a secure source of income, and reducing or simplifying their workload. Connor et al. (2008) and Ward et al. (2008) give the following different classifications of Australian farmers into groups.

Connor et al. (2008) classify farmers as follows:

- 52 percent are business oriented with low environmental concern. These farmers are reliant on their own knowledge and independent in their decision making.
- 22 percent are business oriented and confident in their ability to innovate. These farmers have the highest environmental concern.
- 13 percent are traditionalists and have no environmental concern. These farmers believe that they do not need a high degree of education or training in order to farm effectively.

The remaining 13 percent of farmers are not described.

Ward et al. (2008) classify farmers as follows:

- 52 percent have weak business orientation and low environmental concern. These farmers are the most receptive to social influences on their decision making.
- 25 percent have strong business orientation and are confident in their ability to innovate. These farmers have low environmental concern, are not motivated to learn.
- 10 percent have the weakest business orientation and high environmental concern. These farmers are not receptive to social influences nor motivated to learn.
- 13 percent have the highest environmental concern and willingness to learn. These farmers also face significant capital constraints.

Coleman & Sin (2012) provide a framework for thinking about farmers' decisions to adopt new environmentally friendly technologies. They note that delaying adoption may be an optimal individual decision as it allows farmers to learn from earlier adopters, take advantage of alternative technologies that might arise, and avoid irreversible costs of adopting and locking-in inferior technologies. Where farmers' individual adoption decisions are not socially optimal Coleman & Sin (2012) identify the roles for regulatory intervention to encourage adoption.

Following the development of a new technology, the proportion of the target population who have adopted the technology can be describes using an S-shaped function of the time since the technology became available. Griliches (1957) fits these S-curves with logistic functions and characterizes them according to three aspects: (i) origin, when the population begin to adopt; (ii) slope, the speed of adoption; and (iii) ceiling, the total proportion who adoption.

A common approach when modeling individual firms' adoption decisions is to treat adoption as an irreversible binary decision: in some period firms make a step change from the old technology to the new technology. The key question under this framework is when will firms adopt the new technology? Berger (2001) consider this using an agent-based approach, where as agents learn about the technology from observing other agents they become more likely to adopt it. This is also the framework used by Kerr & Newellz (2003) to assess the ability of regulatory intervention to encourage technology adoption in the context of the U.S. petroleum industry's phase-down of lead in gasoline. The approach by Ellison & Fudenberg (1993) is notable in that, they allow their agents to revise their choice of which technology they will use. Their model contains inertia as only some agents are able to change each period.

In this paper, as part of considering the adoption of specific mitigation practices and technologies, we treat adoption as a continuous decision. Rather than deciding when to adopt, in each period farmers decide how much more they will adopt new practices.

1.2 Nutrient trading schemes

We will frequently discuss the development of our inertia model in the context of a trading scheme for nitrogen emissions. In this section we provide a brief overview of nutrient trading schemes and their application to non-point sources. Readers who are already comfortable with these concepts may wish to move forward to the next section.

The key nutrients emitted by agricultural activities are nitrogen and phosphorus. Increased levels of these nutrients in local water bodies lead to reduced water clarity and increased algal growth. The resulting concentrations of algae lead to eutrophication of water ways, are harmful to fish, and in sufficient quantities can be poisonous to humans and livestock (Carpenter et al. 1998, Parliamentary Commissioner for the Environment 2006).

Nitrogen and phosphorus tend to enter the farming system via the application of fertilizers and the importing of feed for livestock. Some of these nutrients leave the farm as produce: milk, meat, fiber and crops. Of the nutrients that do not leave the farm as produce, a proportion remain in the soil and plants but the rest is lost from the farm as nutrient emissions into local water ways (such as rivers, streams, and lakes) or into groundwater (underground bodies of water).

In New Zealand, farms' nutrient losses can be estimated using the OVERSEER software tool developed by AgResearch (2009). This gives farms' long run average nutrient losses as a function of farm management practices, including: farm type, output produced, stocking rate, fertilizer use, imported feed, area for effluent irrigation, and the use of mitigation technologies (nitrogen inhibitors, wintering and stand-off pads); and farm location, including: slope, rainfall, soil type and drainage.

Under a nitrogen trading scheme the regulator provides a fixed supply of annual allowances. Each allowance entitles the bearer to emit a single unit of nitrogen. At the start of each year, farmers receive or purchase an initial allocation of permits. During the year, farmers are free to buy and sell allowances. At the end of the year, farmers must surrender sufficient allowances to cover the nitrogen emissions from their property for that year. Farmers with insufficient allowances to cover their intended emissions must either purchase unused allowances from farmers with excess allowances, reduce their emissions, or risk non-compliance. By controlling the supply of allowances a regulator can manage the total amount of nitrogen emissions.

A trading scheme is theoretically desirable, as it encourages mitigation to occur where it is most cost effective. Profit-maximizing farmers will mitigate as long as the cost of mitigation is less than the value of the allowances they would otherwise have to hold. This implies that the price of allowances will be such that all allowances are used and each farmer is indifferent between further mitigation and purchasing additional allowances. It follows that under a trading scheme the least costly mitigation activities will take place first.

For a more general introduction to the literature on environmental trading schemes we recommend Tietenberg (2006). Barnes & Breslow (2001) provide a good introduction to the application of emissions trading for air quality, and Kerr et al. (2012) provide a good introduction to the application of nutrient trading for water quality.

2 The Inertia Model

Consider a farmer faced with regulatory pressure to reduce nutrient emissions. The farmer can either adopt new management practices and technologies designed to reduce emissions, or can attempt to reduce emissions given their current practices and technologies.

The adoption of new practices or technologies is potentially threatening to the farmer or the farm business and will involve risk and learning new or unfamiliar abatement activities. In contrast, continuing with current practices and technologies is likely to be less threatening to the farmer and, while costly in the long run, will feel less risky in the short run.

Although the optimal response to nutrient regulation must involve the adoption of appropriate practices and technologies in the long run, farmers are likely to be resistant to making these changes in the short run. We will describe this resistance as inertia. Farmers' inertia will decline with time, as their current system becomes sub-optimal, and as farmers observe their neighbors making changes on their own farms.

The passing of time gives farmers greater opportunity to learn and prepare for change, social and regulatory pressure will increase, and new technologies will become available. There is anecdotal evidence that long established farmers are more resistant to change. As time passes these farmers are more likely to retire, allowing less well established farmers to take their place.

Farming is a business and, while profit does not drive all farming activity, many farmers have significant mortgages to repay. It follows that farmers have some incentive to improve the efficiency of their farm's management by adopting practices and technologies that are consistent with their current activities.

Farmers are often part of the same networks (social or professional) and therefore have opportunities to learn from each other. There is ample evidence in the literature that suggests this takes place. We even have anecdotal evidence that some farmer deliberately delay adopting profitable new technologies in order to capitalize on learning from their peers.

The relative importance of each of the above factors will differ between farmers. Building a model enables us to observe the aggregate impact of nutrient regulation, and the interactions between the decisions of different farmers.

2.1 The general model

We consider a group of farmers subjected to an exogenous cap on total nutrient emissions and who are able to participate in a nutrient trading scheme. In the context of this regulation, we will think of farmers as using two inputs: nutrient allowances (n) and new mitigation technologies or practices (m).

Under the inertia model, farmers have a maximum amount of additional mitigation they are willing to adopt in any given year.

We express the decision problem of farmer i at time t as:

$$\max \pi_{it} = \max_{m_{it}, n_{it}} f_i(m_{it}, n_{it}) - p_t n_{it}$$

where $f_i(\cdot)$ is the farm's profit from production and incorporates the cost of the different levels of mitigation, and p_t is the price of nutrient allowances at time t.

Subject to a binding nutrient cap S_t over all farmers:

$$\sum_i n_{it} \leq S_t$$

And, subject to the farmer's resistance to increasing mitigation:

$$m_{it} - m_{i,t-1} \leq h_i\big(t, m_{i,t-1}, p_{t-1}, \{m_{j,t-1}\}\big)$$

where $h(\cdot)$ gives the maximum increase in mitigation a farmer is willing to undertake ($h(\cdot) \geq 0$), and $\{m_{j,t-1}\}$ is the set of all farmer mitigation decisions in the previous period.

2.2 Production decisions

Given the functional form of a farm's profit function we can determine a farmer's optimal production decision as a function of the price of allowances and the upper bound on mitigation.

We propose the following functional form for farmers' profit from production per hectare. We use this form as it extends the functional form used by Anastasiadis et al. (2011), and can intuitively be decomposed into profit as a function of nitrogen emissions, and a measure of the non-optimality of farmers' current mitigation technologies and practices. It also has continuous first-order derivatives.

$$f_i(m_{it}, n_{it}) = a_i {n_{it}}^2 + b_i n_{it} + c_i + d_i(n_{it} - e_i + m_{it})^2$$

where a_i, b_i, c_i and d_i are coefficients, and e_i is the farm's emissions before regulation.

Figure 1 gives an example of the behavior of this functional form. The green line gives farmers' profit if they have no resistance to change. The blue and orange lines demonstrate farmers' profit functions given bounds on their mitigation.

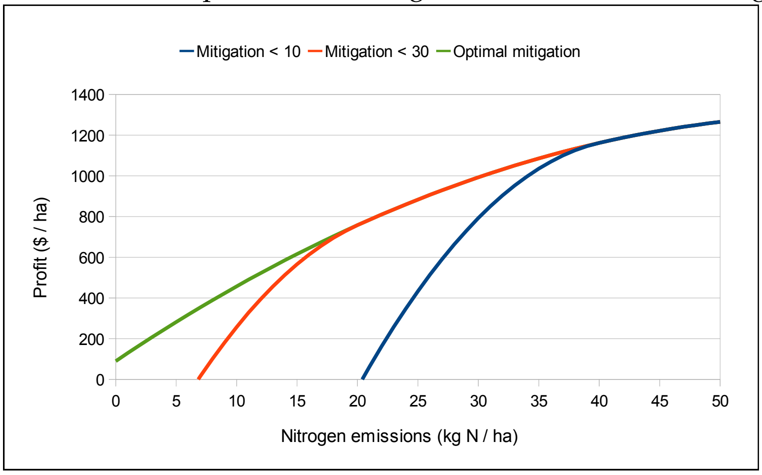

Figure 1. Farm's profit per hectare for different mitigation bounds

Let $\bar{m}$ be the upper bound on m_{it} as determined by $m_{i,t-1}$ and $g(\cdot)$. Then $m_{it} \leq \bar{m}$ and we can determine farmers production decisions as follows:

When $m_{it} < \bar{m}$:

$$\frac{\partial \pi_{it}}{\partial m_{it}} = 0 \text{ implies } \quad -2d_i(n_{it} - e_i + m_{it}) = 0$$

so

$$m^*_{it} = n_{it}$$

And

$$\frac{\partial \pi_{it}}{\partial n_{it}} = 0 \text{ implies } 2a_i n_{it} + b_i - p_t = 0$$

so

$$n^*_{it} = \frac{p_t - b_i}{2a_i}$$

When $m_{it} = \bar{m}$:

$$\frac{\partial \pi_{it}}{\partial n_{it}} = 0 \text{ implies } 2a_i n_{it} + b_i + 2d_i(n_{it} - e_i + \bar{m}) - p_t = 0$$

so

$$n^*_{it} = \frac{p_t - b_i + 2d_i(e_i - \bar{m})}{2a_i + 2d_i}$$

We can show that farmers will hold more allowances when their mitigation decision is constrained ($m_{it} = \bar{m}$) than when their mitigation decision is unconstrained ($m_{it} < \bar{m}$) for the same allowance price. For ease of notation we drop the subscripts in the following proof.

$$\frac{p - b}{2a} \leq \frac{p - b + 2d(e - \bar{m})}{2a + 2d}$$

as

$$
\begin{aligned}
(p-b)(2a+2d) &\leq (p-b+2d(e-\bar{m}))(2a) \\
2d(p-b) &\leq 2d(2a(e-\bar{m})) \\
\frac{p-b}{2a} &\leq e-\bar{m}
\end{aligned}
$$

which must be true whenever $m_{it}^{*}=\bar{m}$.

The first derivative of a farmer's profit function is equivalent to a farmer's demand function (their demand for allowances as a function of price). Figure 2 gives examples of farmers' demand functions that correspond to the example profit functions given in Figure 1.

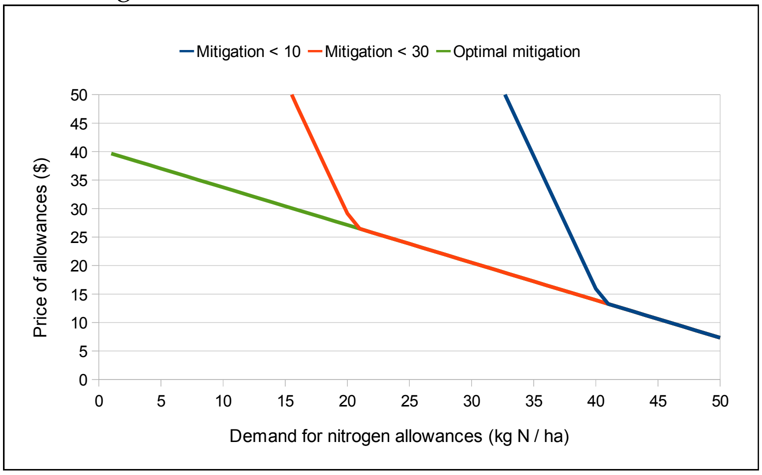

Figure 2. The demand for allowances for different mitigation bounds

Note that we have defined profit and demand on a per hectare basis. When aggregating profit or demand for allowances across multiple farmers we must account for the area of each farm. Notably this changes how we express the binding nutrient cap:

$$
\sum_{i} \eta_i n_{it} \leq S_t
$$

where η_i gives the farm area in hectares, and n_{it} gives emissions per hectare for farm i in year t.

2.3 The inertia function

The choice of the inertia function $h_i(\cdot)$ is independent of the functional form chosen for the farmers' profit functions. In designing an inertia function thought needs to be given to the behavior it should exhibit. How long will farmers maintain their current practices before changing? When farmers are willing to change, how rapidly will they change? Do farmers make many small changes year-to-year or larger less frequent changes? How prevalent are cascade effects (where one farmer's mitigation triggers other farmers to mitigate, who in turn triggers yet more farmers to mitigate)?

It may be helpful when specifying the functional form for farmers' inertia functions to separate inertia into two components: the decision to change, and the maximum amount a willing farmer will change this period.

We propose the following functional form for a deterministic inertia function. We use a linear form for simplicity in the absence of strong priors for any other shape.

$$h_i\big(\tau_i, m_{i,t-1}, p_{t-1}, \{m_{j,t-1}\}_j\big) = \begin{cases} 0 & \text{if} \quad g_{i,t-1} \leq \delta_i \\ g_{i,t-1} - \delta_i & \text{if} \quad g_{i,t-1} > \delta_i \end{cases}$$

With $g_{i,t-1}$ as a measure of how sub-optimal the farmer perceives their mitigation decisions to have been last period.

$$g_{i,t-1} = \alpha_i \tau_i + \beta_i \big(m_{i,t-1} - \frac{p_{t-1} - b_i}{2a_i}\big) + \gamma_i \big(\max_j \{m_{j,t-1}\} - m_{i,t-1}\big)$$

Where α_i, β_i, γ_i and δ_i are coefficients, τ_i gives the time since the farmer last increased mitigation on their farm, and $\frac{p_{t-1}-b_i}{2a_i}$ is the mitigation decision that would have been optimal given last period's price of allowances (the mitigation decision that a farmer would make if their inertia was non-binding, and assuming their mitigation decisions do not influence the price of allowances).

We can interpret α as capturing the frequency with which farmers replace or update their existing farm technologies and review the associated management practices. Farmers with low α values will be more likely to have long delays between changes in mitigation, this may be because they are capital constrained or prefer traditional methods of farming.

We can interpret β as capturing the business focus of the farm. Farmers with high β values will be more likely to increase their mitigation activities when their current practices are suboptimal, this may be because they are more comfortable innovating.

We can interpret γ as capturing a farmer's willingness and ability to learn from other farmers. Farmers with high γ values will be more likely to carry out increased mitigation when other farmers have already done so, this may be because they are socially influenced or risk adverse.

We can interpret δ as capturing overall resistance to change. Farmers with low δ values will be more likely to carry out new mitigation activities, this may be because they have higher environmental concern.

This suggests that the farmer classifications by Connor et al. (2008) and Ward et al. (2008) can be reflected by the inertia model as follows:

- For the farmers classified by Connor et al. (2008):
  - The business oriented farmers would have high β_i values but low γ_i values.
  - The innovative farmers would have even higher β_i values and lower δ_i values.
  - The traditional farmers would have very low β_i and γ_i values.
- For the farmers as classified by Ward et al. (2008):
  - The majority of the farmers would have low β_i values but high γ_i values.
  - The innovative business oriented farmers would have high β_i values and low δ_i values.

- The unresponsive farmers would have low β_i and γ_i values but also low δ_i values.
- The capital constrained farmers would have the lowest α_i values but also the lowest δ_i values.

2.4 Random inertia

While the inertia function may be a good indicator for a farmer's intention to change there may be factors outside a farmer's control that result in actual mitigation differing from intended mitigation. Changes in market conditions, farm staff, or personal circumstances will impact a farmer's ability to realize their intended mitigation. Unfavorable weather conditions may require a farmer to spend more effort maintaining their farm, reducing their ability to prepare and implement new mitigation. Alternatively, there may be unanticipated scale or synergy effects that make the intended mitigation more effective or additional mitigation more worthwhile.

We propose the use of a stochastic functional form, with the same expected value as the deterministic functional form, to estimate the range of possible outcomes we might observe in reality.

$$h_i\big(\tau_i, m_{i,t-1}, p_{t-1}, \{m_{j,t-1}\}_j\big) = \begin{cases} 0 & \text{if} \quad g_i' \leq \delta_i \\ g_i' - \delta_i & \text{if} \quad g_i' > \delta_i \end{cases}$$

Where g_i' is a random variable with expected value $g_{i,t-1}$.

If we think of farmers' mitigation decisions as choosing to implement some technologies out a set of discrete technology choices, then we may allow g_i' to follow a binomial (or multinomial) distribution with the number of trials determined by the number of technologies. If we think of farmers' mitigation decisions as choosing some number of small changes to make, then we may allow g_i' to follow a Poisson distribution with rate parameter $g_{i,t-1}$.

For the purpose of simulating the inertia model when farmers' inertia is stochastic we focus on the case where there is strong (perhaps perfect) correlation between farmers' inertia values. This enables us to consider the variation in outcomes that might arise from shocks to all farmers. These are the more interesting shocks for a regulator whose concern is with the long term overall performance of the region.

It is straightforward to allow farmers' inertia values to be simulated independently of each other. However, given a large sample of farmers the aggregation of independent shocks should have minimal impact on the aggregate performance of all farms, and hence is of minimal interest when considering mitigation at a catchment level, which is our focus in this paper.

3 Implementing the Inertia Model

We will implement the inertia model as an extension of NManager (Anastasiadis et al. 2011). In this section we set out an algorithm for implementing the model and the general behavior we expect the model to result in.

3.1 Solution algorithm

We propose the following algorithm for the model. As farmers inertia in each period depends on their decisions and the price in the previous period, the algorithm solves the model for each period from first to last in sequence.

We normalize farmers' current mitigation and emissions so $m_{i,0} = 0$ and $n_{i,0} = e_i$ for all farmers. In the absence of nutrient regulation we assume $p_0 = 0$, and $\tau_i = 0$ for all farmers.

For each period, we resolve the model in the following order:

1. Recall farmers' decisions from last period $\{m_{j,t-1}\}_j$ and $\{n_{j,t-1}\}_j$ and the market price p_{t-1}.
2. Calculate $g_{i,t-1}$ for each farmer.
3. If the model is stochastic, draw random variables g'_i with expected value $g_{i,t-1}$ for each farmer.
4. Determine $h_i(\cdot)$, and from this farmers' upper bounds on mitigation.
5. Construct the individual demand curves for each farmer.
6. Aggregate farmers' individual demand curves to form a catchment demand curve. Equate aggregate demand with the supply of allowances to determine the market clearing price (p_t).
7. Apply the market clearing price to farmers' individual demand curves to determine the emissions, mitigation and profit for each farmer (n_{it}, m_{it} and π_{it}).
8. Set $\tau_i = 0$ for each farmer who increased their mitigation during the current period, and $\tau_i = \tau_i + 1$ for each farmer who did not.

Of these, only step 6 is not computationally straightforward given the model specification above. If we use quadratic profit functions then farmers' demand curves are monotonic, non-increasing, and piecewise linear, and hence total demand is likewise monotonic, non-increasing, and piecewise linear. There are many ways to determine the intercept of a monotonic, non-increasing, piecewise linear function and a horizontal line. Among them are the modified Newton method used by NManager for this kind of problem, and an adaption of the analytic solution to NManager given in the appendix.

3.2 Expected behavior

Suppose there were to be a step decrease in the total permitted level of nitrogen emissions. This could be driven by the introduction of an nitrogen trading scheme or a decrease in the supply of emission allowances. We anticipate that the inertia model would suggest the following response by farmers:

1. Initial inertia is high. There is minimal increase in mitigation, most farms respond by trying to manage within their current mitigation technology and practices.

2. The price of allowances will be much higher than its long run value.

3. Some farmers' inertia will weaken, motivating them to introduce new mitigation technologies and practices. These farmers will be the ones most motivated by nitrogen prices (the $\beta_i(m_{i,t-1} - \frac{p_{t-1}-b_i}{2a_i})$ component of $g_{i,t-1}$).

4. The price of allowances will decrease as those farmers who carried out mitigation now demand fewer allowances at each price.

5. In response to farmers carrying out mitigation in previous periods, more farmers will introduce new mitigation technologies and practices (driven by the $\gamma_i\big(\max_j\{m_{j,t-1}\} - m_{i,t-1}\big)$ component of $g_{i,t-1}$). This will further lower the price of allowances.

6. Stages three to five will repeat as farmers near the optimal long run response.

7. Those farmers that carried out more mitigation that was optimal in the long run will decrease their use of mitigation technologies and practices as the price of allowances declines.

8. Once farmers are close enough to their optimal long run systems they will increase mitigation infrequently (driven only by the $\alpha_i\tau_i$ component of $g_{i,t-1}$).

The values of the γ, β and α parameters will determine the importance of each of the above steps in any realization of the model. The description given above assumes a balance between the different parameters.

4 Moving Forward

The inertia model we have specified uses aspects of farmers' behavior to determine their mitigation decisions when faced with a price for nitrogen. We have specified our model in both a general and an explicit form.

Given the explicit form of our model, we will next demonstrate the range of possible behaviors that the model can produce before using the model to extend NManager. This should enable us to estimate the cost of reaching a given nitrogen target when farmers' short term response to regulation is less cost effective than their eventual response.

In our model each farmer is described by nine parameters. While it may be difficult to find appropriate data in order to calibrate all nine parameters, we will also make suggestions as to what kind of data would be ideal and how the parameters could be estimated.

References

AgResearch (2009), An introduction to the overseer nutrient budgets model (version 5.4), Technical report, Ministry of Agriculture and Forestry, FertResearch and AgResearch.

Anastasiadis, S., Nauleau, M.-L., Kerr, S., Cox, T. & Rutherford, K. (2011), Does complex hydrology require complex water quality policy? nmanager simulations for lake rotorua, Motu Working Paper 11-14, Motu Economic and Public Policy Research.

Barnes, P. & Breslow, M. (2001), Pie in the sky? the battle for atmospheric scarcity rent, Technical Report 13, Political Economy research Institute. working paper.

Baumgart-Getz, A., Stalker Prokopy, L. & Floress, K. (2012), 'Why farmers adopt best management practice in the united states: A meta-analysis of the adoption literature', *Journal of Environmental Management* **96**, 17–25.

Berger, T. (2001), 'Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis', *Agricultural Economics* **25**, 245–260.

Carpenter, S. R., Caraco, N. F., Correll, D. L., Howarth, R. W., Sharpley, A. N. & Smith, V. H. (1998), 'Nonpoint pollution of surface waters with phosphorus and nitrogen', *Ecological Applications* **8**(3), 559–568.

Coleman, A. & Sin, I. (2012), The adoption of environmentally friendly technologies in agriculture, Technical report, Motu Economic and Public Policy Research. Motu Note.

Conley, T. G. & Udry, C. R. (2003), 'Learning about a new technology: Pineapple in ghana', *American Economic Review* **100**(1), 35–69.

Connor, J. D., Ward, J., Clifton, C., Proctor, W. & Hatton MacDonalda, D. (2008), 'Designing, testing and implementing a trial dryland salinity credit trade scheme', *Ecological Economics* **67**, 574–588.

Dury, J., Garcia, F., Reynaud, A., Therond, O. & JE., B. (2010), Modelling the complexity of the cropping plan decision-making, *in* D. A. Swayne, W. Yang, A. A. Voinov, A. Rizzoli & F. T., eds, 'International Congress on Environmental Modelling and Software Modelling for Environments Sake'.

Ellison, G. & Fudenberg, D. (1993), 'Rules of thumb for social learning', *Journal of Political Economy* **101**(4), 612–643.

Fenemor, A., Sinner, J., Anastasiadis, S., Cradock-Henry, N., Crengle, H., Harris, S., Bright, J., Greenhalgh, S. & Kerr, S. (2012), Simulating market based instruments (mbis) for water allocation and quality in new zealand, Technical report, Landcare, Cawthron and Motu Economic and Public Policy Research.

Foster, A. D. & Rosenzweig, M. R. (1995), 'Learning by doing and learning from others: human capital and technical change in agriculture', *Journal of Political Economy* **103**(6), 1176–1209.

Griliches, Z. (1957), 'hybrid corn: an exploration in the economics of technological change', *Econometrica* **25**(4), 501–522.

Kerr, S., McDonald, h. & Rutherford, K. (2012), Nutrient trading in lake rotorua: a policy prototype, Technical report, Motu Economic and Public Policy Research. Motu note # 10.

Kerr, S. & Newellz, R. G. (2003), 'Policy-induced technology adoption: evidence from the u.s. lead phasedown', *Industrial Economics* **51**(3).

Pannell, D. J., Marshall, G. R., Barr, N., Curtis, A., Vanclay, F. & Wilkinson, R. (2006), 'Understanding and promoting adoption of conservation practices by rural landholders', *Australian Journal of Experimental Agriculture* **46**, 1407–1424.

Parliamentary Commissioner for the Environment (2006), Restoring the rotorua lakes: The ultimate endurance challenge, Technical report, Parliamentary Commissioner for the Environment, Wellington.

Skinner, J. & Staiger, D. (2005), Technology adoption from hybrid corn to beta blockers, Technical Report 11251, NBER working paper series.

Sutton, M., Oenema, O., Erisman, J. W., Leip, A., van Grinsven, H. & Winiwarter, W. (2011), 'Too much of a good thing', *Nature* **472**, 159–161.

Tietenberg, T. H. (2006), *Emissions Trading: Principles and Practice. 2nd ed.*, RFF Press.

Ward, J., Bryan, B., Crossman, N. & King, D. (2008), 'Evidence based farmer decision models to assess the potential for multiple benefit carbon trading'.