Appendix 2: Choice of Catchment Modelling Approach

Catchment optimisation model

This section outlines the selection of the economic-modelling approach employed in this analysis. The model is an optimisation model; that is, an iterative search process is employed to identify how different management activities must change from their current level to minimise the cost incurred by a change in the management environment (e.g. as experienced with the introduction of an N limit). The model used here is a special type of optimisation model, involving a method known as mathematical programming (Bazaraa et al., 2006).

A key type of equation utilised in the form of mathematical modelling that is utilised in this study (mathematical programming) is a constraint. These constraints can define key relationships (i.e. a relational constraint), as in the N loss example above, or can be used to restrict the level of certain decision variables (i.e. a limit constraint). For example, a key relationship used in some models is a limit constraint defining the amount of a contaminant lost from farms in a catchment. This could be defined $nt > N$, where nt is the total nitrogen target (tonnes of nitrogen) and the equation describes that the level of nitrogen lost from the catchment (N) has to be less than this target in the modelled scenario. (This relationship is described for example only; the nitrogen limit within the catchment model described below is introduced by way of allocating entitlements for nitrogen leaching.) To describe a complex reality within a mathematical model, it is necessary to formulate various assumptions that permit people working with the model to develop an understanding of the relationships between certain key levers. Without these assumptions, it is difficult to formulate such an understanding given the uncertainty regarding key relationships. A key purpose of this report is to outline the justification for the key assumptions utilised in this application.

Optimisation in the context of mathematical programming concerns the identification of decision variables that maximise profit for a given set of constraints. Suppose that there is three-equation model: equation 1 describing profit as related to land-use, equation 2 describing nitrogen load as related to land-use, and equation 3 placing an upper limit on nitrogen load. Optimisation involves trying to find the land-use configuration that maximises the level of profit in the catchment, as defined in equation 1, subject to the relationships and bounds defined in equations 2 and 3.

Optimisation through nonlinear programming is used here (Bazaraa et al., 2006). This generally involves the definition of a model in which both the profit specification and constraints contain nonlinear expressions. Solution of this model outlines how land-use and land management must change under different circumstances to mitigate nitrogen loss at least cost. Its structure is loosely based on that of the Land Allocation and Management (LAM) catchment framework (Doole, 2015). The flexibility of this model is demonstrated in its broad utilisation across a number of nonpoint-pollution contexts, both nationally (Doole, 2013; Howard et al., 2013; Holland and Doole, 2014) and internationally (Beverly et al., 2013; Doole et al., 2013a). Key benefits associated with the application of the LAM framework are (Doole, 2015b): (a) its flexible structure allows its broad adaptation to diverse circumstances (for example, the broadly divergent allocation scenarios studied herein); (b) the calibration of the model is done in a straightforward way, to improve clarity and interpretation of model output (see below for further information); (c) the simplicity of the model structure makes it easier to employ in interdisciplinary modelling and participatory work; (d) the complexity of the model can be altered depending on the quality and quantity of resources available; (e) the model can be efficiently coded in popular nonlinear-optimisation software, such as the General Algebraic Modelling System (GAMS) (Brooke et al., 2014), that allows matrix generation; and (f) the use of optimisation allows the use of a consistent and structured objective to select between multiple alternative outcomes within a complex decision problem, encompassing multiple decision makers and complexities regarding diversity in relative profit. The utilisation of optimisation also allows for the straightforward representation of trading activity in a market for nutrient entitlements (Doole et al., 2011).

Optimisation of the economic model identifies the values for decision variables that maximises the total profit earned on farms across the catchment, subject to the constraints defined in the model. The primary decision variables in the model are those representing the area (ha) allocated to each management option within each land-use in each zone. Primary constraints are those limiting the land-use in a given zone to the area available within that spatial area. Total profit is determined through multiplication of the area of each land-use option employed and its associated level of profit per ha. The total nitrogen load is computed through the multiplication of the area of each land-use option employed and the nitrogen leaching load per ha associated with each management option. With the introduction of a limit on nitrogen leaching, the area of each land-use utilised for a mitigation option, rather than a baseline (current) management option, will typically increase. This will concomitantly reduce nitrogen loss from that land area, but also increase/decrease profit. In some cases, it may be more cost-effective to change land-use away from the current land-use, in order to achieve a given nitrogen-leaching target at the catchment level. In this model, the limit for leaching is implemented through the representation of permits required for representative farms to leach, which are allocated among the population according to diverse systems (see below).

The optimisation model focuses on alternative steady-state or equilibrium outcomes. That is, it does not study the transition pathways between the current state and where alternative policy outcomes are predicted to lead. Indeed, it focuses solely on characterising just the equilibria themselves. This approach is consistent with standard practice regarding the economic evaluation of alternative environmental policy instruments (e.g. Hanley et al., 2007; Daigneault et al., 2012; Doole, 2013). It is possible to incorporate the study of temporal processes, such that the time path of adaptation practices can be characterised and then considered during evaluation (Pindyck, 2007). However, this is rare in practice, especially in the evaluation of regional policy, because (a) there is little empirical work available that characterises how farmers in the Lake Rotorua catchment would be expected to adapt to limits, (b) the scarcity of data is compounded when variation over time in key drivers of management behaviour (e.g. output price, input price, productivity, climate, innovation) is high and difficult to predict, (c) dynamic models are difficult to develop and utilise (Doole and Pannell, 2008), and (d) output from dynamic models is heavily biased by the initial and terminal conditions defined during model formulation (Klein-Haneveld and Stegeman, 2005). Overall, these issues provide a strong justification for the employment of a steady-state modelling framework.

Nevertheless, alternative approaches for the economic evaluation of environmental policy instruments exist.

Alternative approaches considered

A key alternate method involves the specification of a simple simulation model, commonly constructed in a spreadsheet and consisting of fewer than 25 equations. In sharp contrast to the model applied here, this would mean representing only a low number of land-uses and spatial parcels within the Lake Rotorua catchment. Indeed, while the LAM model applied here provides a much more refined characterisation of the catchment relative to these approaches (see below), it incorporates thousands of equations that complicate its development and interpretation (e.g. Doole, 2013). The output of a simple simulation model is typically explored using a set of agreed scenarios, as a central part of a participatory-modelling exercise conducted alongside stakeholders (Harris and Snelder, 2014). The goal of this approach is to provide greater clarity to a stakeholder group within a deliberative process, thereby improving their capacity to understand the key relationships central to the complex nonpoint-pollution problem faced within the catchment of interest. Indeed, it proactively deals with the high levels of uncertainty regarding input information, through focusing on simple relationships for which broad levels of agreement among stakeholders are present. However, it is less appropriate for the study of alternative allocation systems within the Lake Rotorua catchment relative to the LAM framework, because of the need to represent a significant number of alternative enterprise types and zones (that vary according to slope, rainfall, and soil type) to provide a rich description of the implications of alternative allocation and trading scenarios. Indeed, if such richness were not portrayed, then the portrayal of any market dynamics would be flawed given a dearth of heterogeneity in abatement cost that is required to drive the operation of an efficient trading mechanism for nutrient entitlements (Doole, 2010). Nevertheless, while an optimisation approach is used as a central part of the LAM application to identify the least-cost means of achieving a given objective with regards to a reduction in nitrogen loss, discrete scenarios associated with alternative allocation systems and expected levels of land-use change (as central to the use of this alternative simulation approach) are adopted. This helps to convey to the stakeholder group the relative importance of different policy mechanisms and institutional barriers.

A preference for the adoption of an optimisation approach also highlights the potential to utilise the NZFARM (New Zealand Forestry and Agriculture Regional Model) (Daigneault et al., 2012, 2014) framework. The LAM and NZFARM models are very similar, in that they both are strongly related to the standard neoclassical approach to evaluating catchment-level environmental policies utilising mathematical programming (Wade and Heady, 1978). However, they differ markedly in their approach to calibration—the method used to ensure that the model returns the current land-use allocation. In contrast to the LAM framework, the NZFARM model employs a series of nonlinear functions—within a broad approach known as positive mathematical programming (PMP) (Howitt, 1995)—that direct a model to return an observed baseline land-use allocation, by manipulating the relative profitability of each individual land-use (Daigneault et al., 2012). Doole and Marsh (2014a, b) have recently highlighted how the NZFARM model may produce misleading results, due to its reliance on this method for calibrating the baseline land-use allocation. Their concern rests around five key issues:

1. There is an infinite number of sets of calibration function parameters that can generate the observed baseline land-use (Heckelei and Wolff, 2003).
2. Calibration does not use any information on how the relative value of land-uses changes as land-use allocation moves away from the observed baseline (Heckelei and Britz, 2000, 2005; Heckelei, 2002). Each one of the infinite sets of calibration function parameters—from which one is arbitrarily selected to calibrate the model to baseline data—yields a different policy response from the calibrated model. Thus, the way in which the model performs outside of the calibrated scenario is completely unpredictable (Heckelei, 2002).
3. The theoretical basis of PMP is, "weak or at least not apparent" (Heckelei and Wolff, 2003, p. 28).
4. The relative value of alternative land-use activities is altered through the introduction of calibration functions.
5. Functional forms used for calibration functions in PMP implementations are generally ad-hoc and difficult to justify (Heckelei and Wolff, 2003; Heckelei et al., 2012).

Daigneault et al. (2014), in response to the article generated by Doole and Marsh (2014a), highlighted that, "We use shadow prices from calibration constraints to obtain the difference between average and marginal returns to specify the parameters" (p. 2). This is noteworthy since it is this approach to PMP that has now been invalidated after a decade of theoretical and applied research (Heckelei, 2002; Heckelei et al., 2012).

In contrast, the LAM model is developed according to the philosophy that: (a) appropriate calibration functions are non-trivial to develop; (b) they introduce inherent bias in scenarios away from the reported baseline (de Frahan et al., 2007); (c) they are difficult to explain to stakeholders, even those with training in economics; and (d) they distort the primary profit data that is a key input to the model. In the LAM framework, the division of each subcatchment into separate parcels—each containing individual representative farming systems—and the definition of appropriate transition costs avoids the need for calibration functions to balance land-use, and hence the bias these additions represent. Accordingly, land-use change is considered as a key part of scenario generation, with the type of alternative land-use and the specification of bounds for which changes in this alternative land-use can be exercised being important inputs to an iterative discussion regarding land-use change dynamics. Indeed, in this way, the specification of land-use change provides an opportunity for collaborative learning of the implications of changes in this important aspect of the overall mitigation approach employed. An evident limitation of this approach is that it does not consider explicitly historical trends regarding land-use change. Nevertheless, given that the introduction of nitrogen-leaching limits will alter the trajectory of land-use change relative to historical trends—in a way that is difficult to predict *a priori* (Lamblin et al., 2000)—the limitations associated with a more straightforward and clear specification are greatly reduced. Moreover, it overcomes the need to employ calibration functions that can provide smooth, but arbitrary and unjustified, responses outside of the status quo situation.

An additional alternative is the adoption of a systems-dynamic approach (e.g. Hart et al., 2013). This method involves the development of an integrated model that attempts to richly describe a broad range of factors associated with addressing a nonpoint-pollution problem, including biodiversity, climate, demography, economics, hydrology, and land-use. For example, the Waikato Integrated Scenario Explorer (WISE) model (Hart et al., 2013) incorporates a land-use model that determines how transition between alternative enterprises occurs under different circumstances. Within this model, the supply of land is dependent on land suitability, the proximity of other enterprises, and zoning restrictions, while the demand for land is driven by economic forces. Such an approach is unsuitable for this application given that system-dynamics models (a) provide no straightforward means to study allocation mechanisms for leaching entitlements given the absence of many key relationships (especially regarding the cost and leaching implications of alternative mitigation options); (b) no such framework has been constructed for the Lake Rotorua catchment and the time and cost required are above those levels available for this application; (c) system-dynamics models provide a rich description of many processes, for which data is scarce in the study region and may be of only little relevance to the problem studied here; and (d) the dynamic processes studied within a systems-dynamics model introduce procedural difficulties, with respect to the complications associated with studying transition, that are outlined above. Accordingly, the equilibrium approach utilised within the LAM model is favoured, relative to this approach.

Agent-based models are another alternative. These involve the representation of individual farms and farmers, with each producer represented as a given type associated with a set of explicit behavioural rules guiding their decisions and interactions with others. These models have been applied throughout New Zealand; for example, in Canterbury (Daigneault and Morgan, 2012), Hawkes Bay (Schilling et al., 2012), Southland (NZIER, 2014), Taupo (Anastasiadis et al., 2013), and Waikato (Doole, 2010). Such frameworks provide a very rich description of individual agents, with diversity represented in risk aversion, personal networks, management objectives, and production-system intensity, among other factors. An agent-based framework is not utilised here because of a lack of suitable empirical data that can be used to generate a realistic description of the personal characteristics of diverse individual producers within the study region and/or allow a validation of model predictions outside of the baseline situation. These are common constraints accruing to the application of agent-based models (Windrum et al., 2007), but are particularly relevant in New Zealand because of privacy restrictions, integral data being held across diverse organisations (Doole et al., 2011), and the significant cost and time associated with collecting suitable data from producer populations to inform model development.