TECHNICAL NOTE:

AN ASSESSMENT OF MITAGATOR: A FARM-SCALE TOOL TO ESTIMATE AND MANAGE THE LOSS OF CONTAMINANTS FROM LAND TO WATER

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ABSTRACT. *Land users and managers require decision support tools (DSTs) that enable them to estimate losses of contaminants from land to freshwater. MitAgator is a DST that estimates losses of nitrogen (N), phosphorus (P), sediment, and fecal indicator bacteria (*E. coli*) and the cost-effectiveness of different strategies to mitigate losses so that a water quality target can be met at the least cost. Some of the algorithms present within Overseer (a standard DST used in New Zealand for N and P management) have been modified and appended to include spatial analysis in MitAgator. Outputs from MitAgator showed good ($R^2 > 0.77$; $p < 0.001$) prediction of measured N and P losses across a range of land uses, but accuracy decreased at larger (catchment) scales. Analysis for P outputs indicated that the most sensitive inputs were hydrological characteristics, followed by soil characteristics and P inputs. Although national databases are used for many of these inputs, if better local data are available, then they should be used. Furthermore, while MitAgator is easy to use by a novice, MitAgator outputs should only be interpreted in collaboration with an experienced user so that limitations concerning cost-effectiveness estimates and spatial and temporal scales are not exceeded.*

Keywords. E. coli*, Good management practices (GMPs), Mitigation measures, Nitrogen, Phosphorus, Sediment.*

Tensions are arising between farming practices and environmental policy in New Zealand and other developed countries worldwide. With the need to produce more food, but remain profitable within catchment water quality limits, tools are required that model contaminant emissions from land to water.

Some tools are available that estimate farm losses of contaminants such as nitrogen (N), phosphorus (P), and sediment at the farm and/or catchment scale (Hewett et al., 2009; Pangopoulos et al., 2012). Some (e.g., Farmscoper; Gooday et al., 2014) combine cost curves for strategies to mitigate contaminant losses with optimization procedures to minimize the potential cost. These tools vary in their sophistication, data needs, ease of use, and output (e.g., losses, but not cost estimates, or vice-versa). To be effective in guiding farming practices and improving water quality, such tools should accurately capture the complexity of edaphic (e.g., catchment characteristics, climate) and farm management systems, use readily available data, consider costs involved in actions to mitigate losses, and be flexible enough to provide recommendations tailored to an individual needs.

In New Zealand, the decision support tool (DST) OVERSEER Nutrient Budgets (Overseer) is used as an industry standard for recommending nutrient inputs and estimating nutrient losses to water at the farm scale (Wheeler et al., 2014). Overseer is also used by many provincial regulatory authorities as a tool to enforce limits on nutrient losses and maintain or improve catchment water quality (e.g., ORC, 2014). However, Overseer cannot spatially identify where contaminants originate on an enterprise (i.e., a farm). Furthermore, there is increasing evidence that many contaminants come from small areas, called critical source areas, of a catchment or farm's total area (McDowell et al., 2014). By targeting critical source areas, the cost-effectiveness of strategies to mitigate contaminant loss from land to water can be significantly im-

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proved over an untargeted approach. Overseer cannot target critical source areas. Nevertheless, in setting up Overseer for an enterprise, a large amount of information is gained on the enterprise operation. Overseer also works on an annual time step, which is well aligned to strategic decisions and the measurement of how an enterprise would make changes to conform to a catchment water quality objective. Hence, our aim was to extend the approach used by Overseer to develop a software-based DST that estimates and maps the relative risks of N, P, sediment, and fecal indicator bacteria (*E. coli*) loss from land to water, estimates the cost and effectiveness of specific strategies to mitigate losses, and provides an optimal mix of the best strategies to reach a specific target, which can be either a percentage decrease in contaminant loss or a relative decrease in load achievable within a budget ($ ha^{-1}). This technical note outlines the structure and function, a comparison of modeled losses against measured losses, and a sensitivity analysis of outputs for the software DST MitAgator. For brevity, focus is placed on how well this tool estimates losses of N, and more fully P, from agricultural land across a range of scales.

Structure and Function

The inputs to MitAgator are derived from Overseer files that provide management data (e.g., stocking rates, fertilizer applications) and national databases (e.g., Land Cover Database 4; LRIS, 2014) that provide physical site characteristics (e.g., soil types; Lilburne et al., 2004). Additional data can be input by the user when they are known to be of better quality. For instance, the user may have soil test data that are either more recent or at a finer spatial scale than present in an Overseer file (fig. 1). These data are used to create a map package that is fed into the application that controls interaction between the databases, the MitAgator engine, and visualization. The engine contains algorithms from published studies (McDowell et al., 2005, 2008; Dymond, 2010; Rutherford and Wheeler, 2011; Wheeler et al., 2011; Muirhead, 2014) that estimate losses to surface waterways for *E. coli*, N, P, and sediment from each parcel of land.

Outputs are projected as a map of estimated annual losses (in kg for N, P, and sediment losses and as low, medium, and high relative risk for *E. coli* losses) divided into 20% quantiles for each contaminant. The uppermost quantile (or risk category) highlights critical source areas, i.e., areas that account for a high proportion of losses but occupy a relatively small proportion of the farm, block, or paddock (whichever is selected as the area of interest) (fig. 2).

After generating loss maps, estimates for mitigating losses occur in two steps. The user first defines the mitigation area. This can be the whole farm, a block within the farm (i.e., a group of fields under similar management), a single field, or a quantile of critical source areas. Second, the user can impose a single mitigation or several mitigations from a list attuned to a specific contaminant, or set a target based on a desired percentage decrease (e.g., 40% less N loss) or cost (e.g., $ ha^{-1}) and let an automated linear optimization routine provide the optimal mix of strategies to meet the target. The effectiveness and cost of each mitigation strategy is based on empirical data with uncertainties calculated as 95% confidence intervals for studies of each mitigation strategy conducted across New Zealand (McDowell, 2014). After applying mitigation strategies to the targeted area, additional outputs are provided as a new map of estimated losses, histograms for load decreases compared to the targeted area, and estimates of the upper and lower values for costs and efficiencies.

The automated linear optimization routine selects a set of compatible mitigation strategies that maximizes the mitigation of contaminant losses for a given cost or that min-

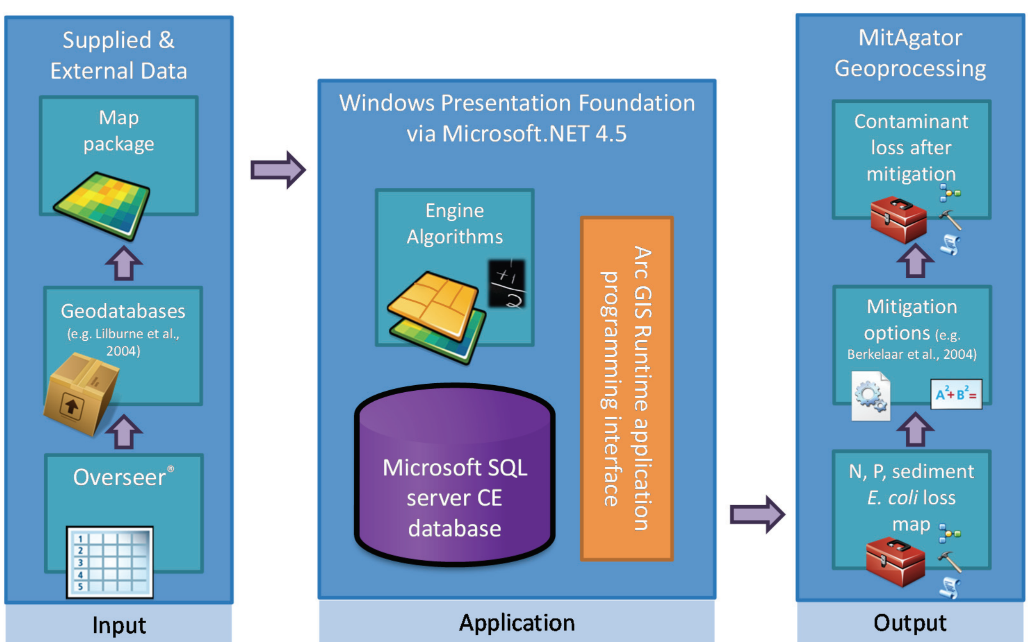

Figure 1. Schematic diagram of MitAgator.

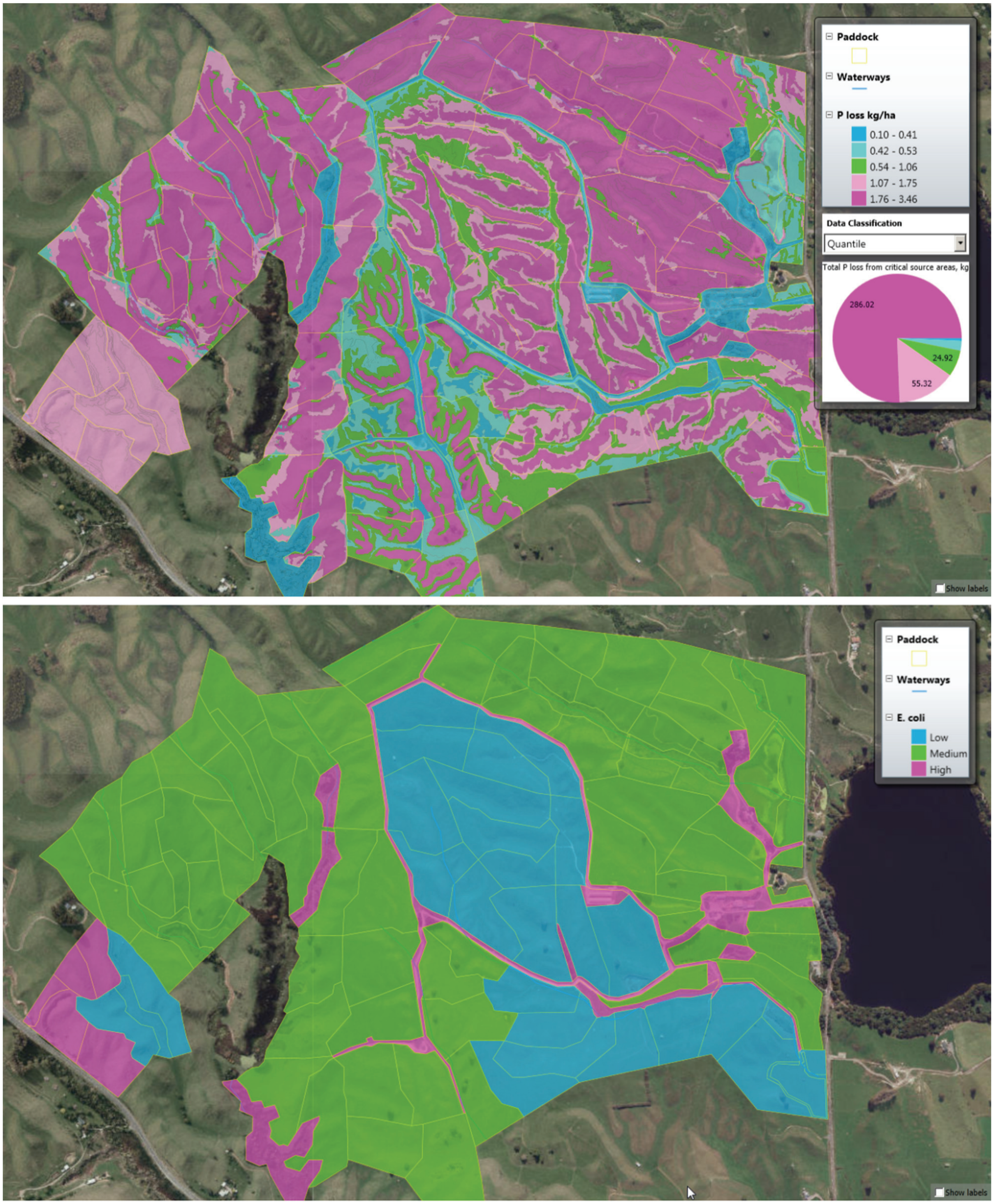

Figure 2. Example map of estimated P (top) and *E. coli* (bottom) losses from a property. Losses are classified by quantiles (kg P ha^{-1} year^{-1}) or risk category (low, medium, and high *E. coli* loss), with the uppermost quantile or risk category identifying critical source areas of P or *E. coli* loss.

imizes the cost for a given level of mitigation. The program achieves this via linear programming methodology, using the open source lpsolve package (Berkelaar et al., 2004). Within the program, compatible combinations of mitigation strategies are added to a linear programming formulation involving binary variables and special ordered sets of type 1 (SOS1; http://lpsolve.sourceforge.net/5.5/LPBasics.htm). The combination of strategies that constitutes the optimal solution is then found by lpsolve using a branch and bound solution strategy, with carefully chosen branch and bound parameters to ensure sufficient solution speed.

COMPARISON TO MEASURED LOSSES

As part of a corroboration exercise, 48 measured annual losses were compared with those estimated by MitAgator. The software uses algorithms from Overseer (the farm-scale standard for N and P loss estimates in New Zealand) that have been modified so they are spatially relevant. For brevity, measured losses were only compared for N and P; comparisons of MitAgator outputs and measured losses for *E. coli* and sediment can be found in sub-models presented by Muirhead (2014) and Dymond (2010), respectively. Losses from a range of locations (from the northernmost and southernmost provinces of New Zealand) and scales were included. Spatially, N losses were spread between 10 plot (<1 ha), 7 field (1 to 10 ha), 7 block (10 to 100 ha, 13 farm (100 to 1000 ha), and 8 catchment (>1000 ha) scales. The number of farm, field, block, and catchment scale studies measuring P losses was 11, 8, 12, and 9, respectively. A range of soil orders (including Allophanic, Brown, Gley, Pallic, Podzol, and Pumice; New Zealand soil classification) and land uses (dairy, red deer, forested, mixed sheep, and beef farm types) were represented (fig. 3).

CORROBORATION

It is important to note that the algorithms obtained from Overseer estimate N losses from the root zone and P losses up to second-order streams, whereas the measured losses were from small, hydrologically isolated plots (<1 ha) to large catchments that integrate sources and sinks over a large area. It is therefore of no surprise that the estimates tended to be poorer with increasing spatial scale or at high rainfall (>1200 mm) with less predictable hydrology (fig. 4). Nevertheless, N and P losses were predicted with reasonable accuracy ($R^2 > 0.77$; $p < 0.001$; fig. 4). Significant relationships can be found for measured versus predicted sediment and *E. coli* losses (Dymond, 2010; Muirhead, 2014). Moreover, the need for better spatial representation and for estimates of sediment and *E. coli* losses (in addition to N and P losses) were major reasons for the development of MitAgator beyond what could be estimated with DSTs such as Overseer.

SENSITIVITY ANALYSIS

A sensitivity analysis was conducted to determine which of up to 20 input factors had the most leverage on estimated P losses from eight different enterprises (table 1) and to serve as a check for developers that sensitive factors had good-quality data. Sensitivity analyses were conducted by incrementally varying numerical inputs by 50%, 75%, 100%, 150%, and 200% greater or less than the initial state (table 1). Categorical variables (e.g., use of forage crops, use of tile drain, and use of flood irrigation) were altered

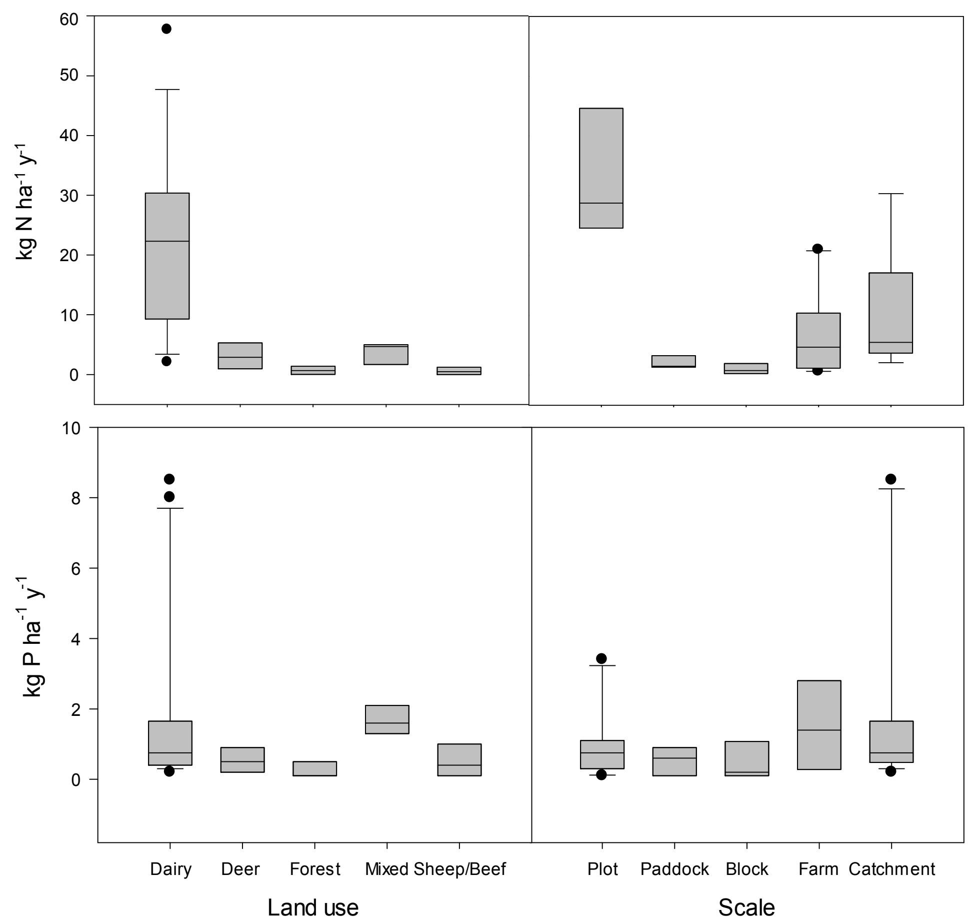

Figure 3. Measured N and P losses according to land use (left) and scale (right). The top and bottom of the boxes represent the 25th and 75th percentiles, respectively; whiskers represent the 10th and 90th percentiles (where calculated), the circles are outliers, and the line inside the box is the median value. Note that variation in plot-scale losses is skewed by studies of forage crop blocks.

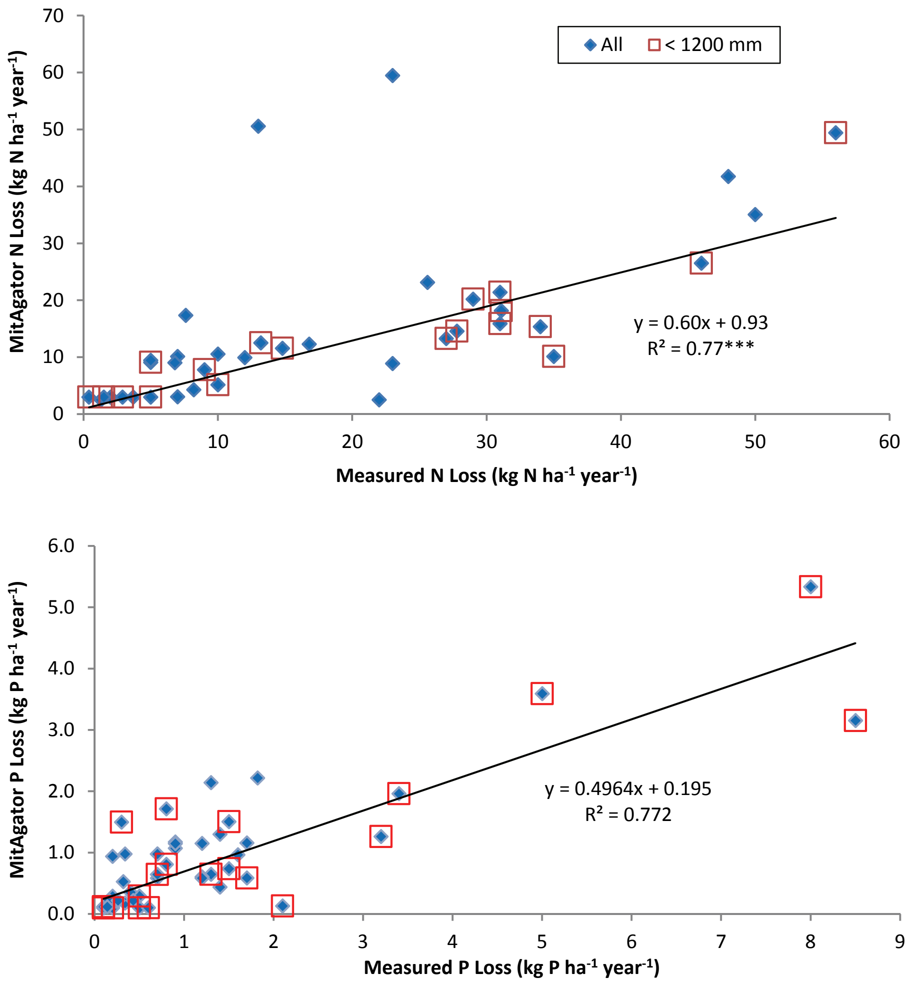

Figure 4. Comparison of measured N and P losses for different land uses against those estimated by MitAgator. The regression is fitted for data with rainfall <1200 mm. Coefficients of determination for relationships including all data were 0.42 and 0.71, respectively.

through all of their categories, as were binary (yes/no) variables. The interaction of up to two variables was also tested. This resulted in 90 million combinations of factors. For analysis, a 1/100 random sample was taken. This data set of 900,000 results was analyzed to determine the size of the main effects and the two-way interactions. The variate analyzed was the natural log of the P loss. The data were analyzed using Genstat (16th edition; https://www.vsni.co.uk/software/genstat/).

Figure 5 shows an example sensitivity analysis for P losses from enterprise 3 (an irrigated dairy farm). Outputs for all enterprises generally had hydrological variables (e.g., rainfall or drainage class) as the most sensitive, followed by soil characteristics (e.g., slope and anion storage capacity) and application rates of P inputs (kg P ha^{-1} year^{-1}). Hydrological variables in addition to slope all strongly influenced surface runoff. Other variables of high sensitivity to outputs were enterprise specific and included fence-line pacing in the deer farm and the use of forage crops on the deer, sheep, and beef farms.

Limitations

Although MitAgator is designed to be operated by a novice, it still relies on the user having quality input data (including a correct Overseer file). Hence, outputs should be interpreted in collaboration with an experienced user. There are several limitations beyond which the model will give poor results. For instance, it may be tempting to apply MitAgator to a large catchment, albeit as a mosaic of smaller sub-catchments. However, a more appropriate choice would be a model such as CLUES (Woods et al., 2006) and SPARROW (Preston et al., 2011) that can account for in-stream attenuation in New Zealand catchment networks.

Another limitation is the temporal estimation of annual losses and mitigation performance. Losses and mitigation performance may both be subject to wide variation according to, for instance, large runoff events that account for the majority of loss but only occur over a few days. Furthermore, there may be time lags in the generation of contaminant losses associated with a land use change or in the mitigation of losses. Due to the use of Overseer algorithms, MitAgator

Table 1. Initial state of variables included in the sensitivity analysis for P losses from eight different enterprise types.

	Enterprise							
	1	2	3	4	5	6	7	8
Variable[a]	Sheep and beef	Deer	Dairy (irrigated)	Dairy (dryland)	Wheat-fallow-wheat	Wheat-winter crop-wheat	Kiwifruit	Forestry
Soil Olsen P concentration (mg L^{-1})	15	20	30	40	30	30	30	10
Slope (class)	Rolling	Rolling	Flat	Flat	Flat	Flat	Flat	Easy
Rainfall (mm)	1100	1100	700	1100	800	800	1100	1100
Irrigation (mm)	-[b]	-	600	-	100	100	-	-
Soil drainage class	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate
Anion storage capacity (0% to 100%)	30	30	30	30	30	30	50	50
P fertilizer applied (kg P ha^{-1})	20	25	40	40	30	30	30	5
Timing and type of P application (vis-à-vis risk month for loss)	Low	Low	Low	Low	Low	Low	Low	Low
Dairy shed effluent applied (kg P ha^{-1})	-	-	10	10	-	-	-	-
Month of effluent application (risk)	-	-	Moderate	Moderate	-	-	-	-
Good storage capacity for effluent	-	-	Yes/No	Yes/No	-	-	-	-
Use of artificial drainage	Yes/No	Yes/No	Yes/No	Yes/No	-	-	-	-
Wallowing	-	Yes/No	-	-	-	-	-	-
Soil organic C (%)	5%	5%	5%	5%	3%	3%	5%	5%
Use of forage crops:								
Winter (% of farm)	10	10	10	10	-	-	-	-
Summer (% of farm)	10	10	10	10	-	-	-	-
Clay (%)	15	15	15	15	15	15	15	15
Use of flood irrigation (border dyke)	Yes/No	-	Yes/No	-	-	-	-	-
Fence-line pacing	-	Yes/No	-	-	-	-	-	-

[a] See MPI (2014) and www.overseer.org.nz for fuller explanation of categorical and binary variables.

[b] Not applicable.

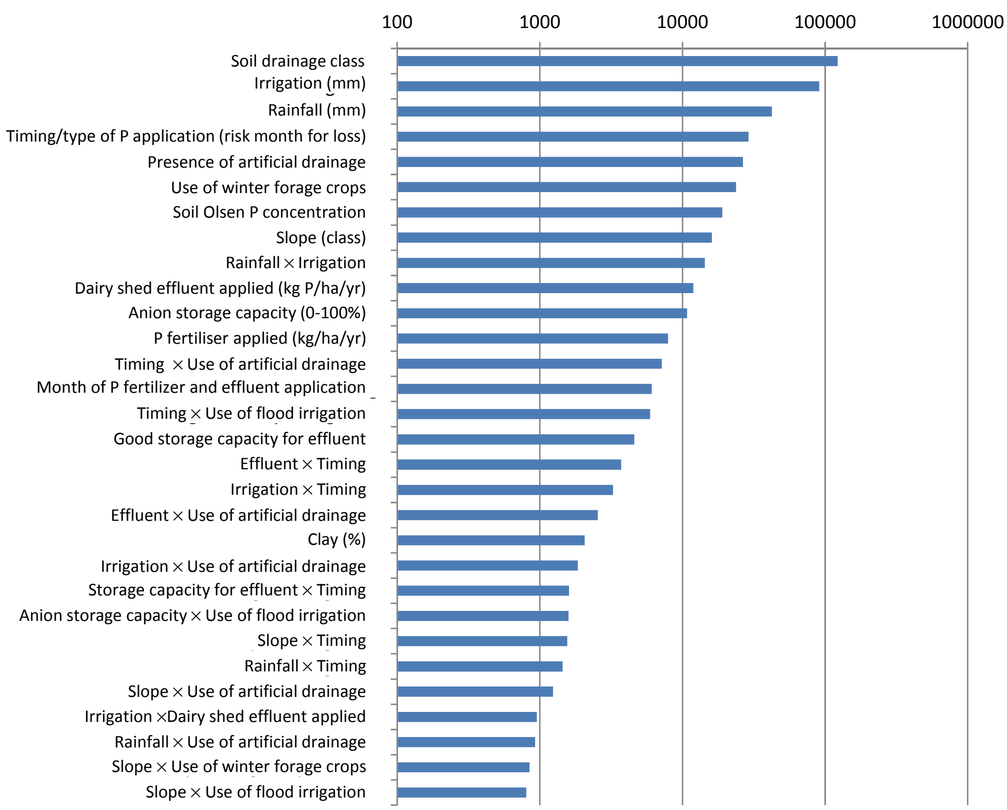

Figure 5. Effects measured as the F ratio statistic for variation of variables in the estimation of P losses by MitAgator for enterprise 3 (irrigated dairy farm). Note the log scale on the *y*-axis. See McDowell et al. (2005) and MPI (2014) for an explanation of each variable.

assumes that both the generation of contaminant losses and the effect of mitigation strategies are at steady state.

However, it is also important that MitAgator outputs that have been recommended by an experienced user are discussed and challenged (if necessary) by the land user or manager. Only those who use the land day-by-day will be able to determine if the cost estimates or indeed the practicality of a specific mitigation strategy or group of strategies are realistic. Because the model is bound to empirical data, it may only be representative of the locations where the experiments were conducted. In such cases, users can input their own estimates of the cost of mitigation strategies.

CONCLUSIONS

Analysis of outputs suggests that variation in contaminant (e.g., N and P) losses can be predicted ($R^2 > 0.77$; $p < 0.001$) by MitAgator at the block and farm scale, with less certainty at the catchment scale and at higher rainfall rates. An example sensitivity analysis indicated that the most sensitive factors for P, and therefore those that should have the best-quality data to ensure accurate outputs, were associated with hydrology, followed by soil characteristics and finally P inputs. The intent is that MitAgator can act as part of a package of tools to help farmers minimize the cost of complying with water quality standards being developed as part of the National Policy Statement on Freshwater Management in New Zealand (MfE, 2014).

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