MITAGATOR^{TM}: A TOOL TO ESTIMATE AND MITIGATE THE LOSS OF CONTAMINANTS FROM LAND TO WATER

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Abstract
Land users and managers require decision support tools (DST) that enable them to estimate losses of contaminants to freshwater. MitAgator^{TM} is a DST that estimates losses of nitrogen, phosphorous, 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 least cost. Some of the algorithms present within the DST Overseer® (a standard DST used in New Zealand for N and P management) have been modified and appended to have spatial capacity for use in the beta version of MitAgator^{TM}. Outputs from MitAgator^{TM} showed good (P<0.001) prediction of measured P and N losses across a range of land uses (in this paper, and for sediment and *E. coli* in other papers. However, accuracy decreased at larger (catchment) scales. A sensitivity 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, if better local data is available, then it should be used. Furthermore, while easy to use by a novice, outputs of MitAgator^{TM} should only be interpreted in collaboration with an experienced user so that limitations around cost-effectiveness estimates and spatial and temporal scales are not exceeded.

Keywords: Good Management Practices (GMPs), *E. coli*, Nitrogen, Phosphorus, Sediment.

Introduction

Tensions are arising between farming practices and environmental policy. 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), also append 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 individuals need.

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 (Wheeler et al., 2014). It is also used by many provincial regulatory authorities as a tool to enforce limits on nutrients losses and maintain or improve catchment water quality (e.g. Otago Regional Council, 2014). However, Overseer cannot spatially identify where on an enterprise (viz. farm) contaminants come from. Furthermore, with increasing evidence that many contaminants come from a minority of a catchment or farm's area (called critical source areas; McDowell et al., 2014), Overseer is not able to improve the cost-effectiveness of mitigation strategies by focusing them on critical source areas. However, in setting up Overseer for an enterprise a large amount of information is gained on how the enterprise operates. 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 objective was to extend the approach used by Overseer in developing a software-based decision support tool that estimates and maps the relative risk 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 - either a percentage decrease in contaminant loss or relative decrease in load achievable within a budget ($ ha^{-1}). This paper outlines the structure and function, comparison to measured losses, and sensitivity analysis of outputs from the software termed - MitAgator^{TM}. For brevity, focus is placed on how well this tool estimates losses of P from agricultural land across a range of scales.

Structure and function

The inputs to MitAgator^{TM} 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 where it is known to be of better quality. For instance, the user may have soil test data that is either more recent or at a finer spatial scale than present in the Overseer file. These data are used to create a map package that is fed into the application that controls interaction between databases, the MitAgator^{TM} engine and visualization. The engine contains algorithms from published studies (Dymond et al., 2010; McDowell et al., 2005; McDowell et al., 2008; Muirhead, 2014; Wheeler et al., 2011) 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 (kg for N, P and sediment losses and a relative risk of low, medium and high for *E. coli* losses) broken into 20% quantiles for each contaminant. The uppermost quantile 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. 1).

After generating loss maps, estimates for mitigating losses occur in two steps. The user firstly defines the area over which losses are to be mitigated. This can be the whole farm, a block (group) within the farm of fields under similar management, a single field, or a quantile such as 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 percentage decrease desired (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 the 95% confidence intervals for studies of each mitigation strategy conducted across New Zealand (see McDowell, 2014). After applying mitigation strategies to the targeted area, additional outputs are provided as a new map of estimated losses together with histograms for load decreases compared to the targeted area and estimates of the upper and lower range of costs and efficiencies.

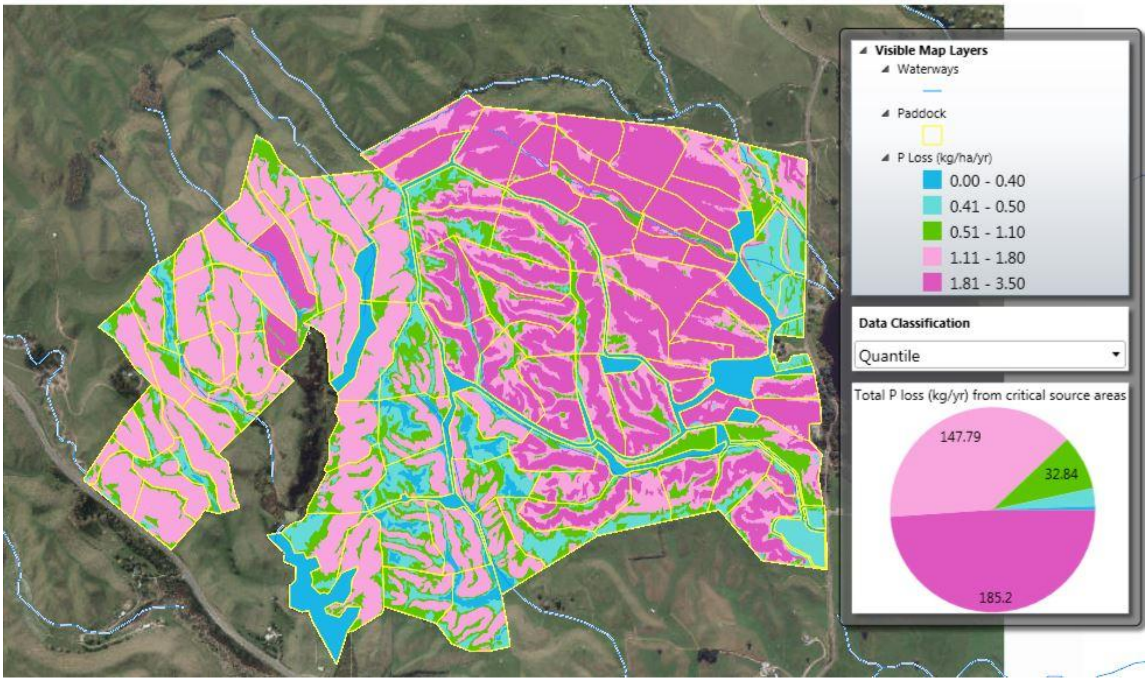


Fig. 1. Example map of the estimated P losses from a property as classified by quantiles (kg P ha^{-1} yr^{-1}).

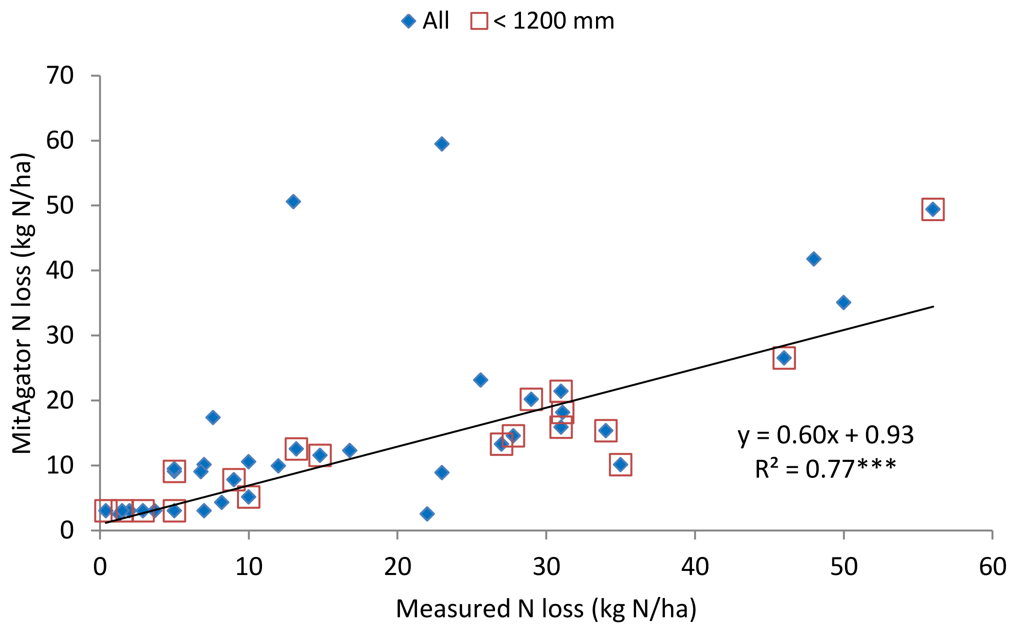
The automated linear optimization routine selects a set of compatible mitigation strategies which maximizes the mitigation of contaminant losses for a given cost, or which minimizes the cost for a given level of mitigation. The program achieves this via linear programming methodology, using the open 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 One (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.

Corroboration

Comparison to measured losses

As part of a corroboration exercise, 48 measured losses were compared against 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 P and N; comparison of algorithms used in MitAgator™ and measured *E. coli* and sediment losses can be found in Muirhead (2014) and Dymond et al. (2010), respectively. Losses from a range of locations (from the northernmost and southernmost provinces of New Zealand) and scales were included. Spatially, losses were spread between 11 plot (< 1 ha), 8 field (1-10 ha), 8 block (10-100 ha, 12 farm (100-1000 ha) and 9 catchment (>1000 ha) scales. A range of soil orders (including Allophanic, Brown, Gley, Pallic, Podzol and Pumice; New Zealand soil classification) and land uses (dairy, red deer, forested, and mixed sheep and beef farm types) were represented.

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



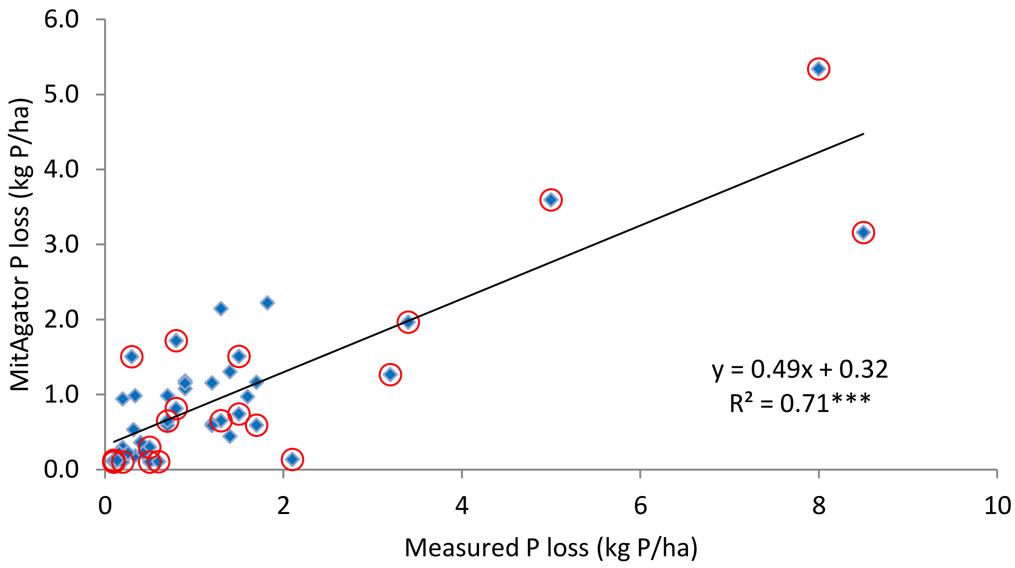


Fig. 2. Comparison of measured P and N losses of different landuses against those estimated by MitAgator^{TM}. The regression is fitted for data (circled) with rainfall < 1200 mm.

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

	Enterprise							
	1	2	3	4	5	6	7	8
Variable[1]	Sheep & 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)	-[2]	-	600	-	100	100	-	-
Soil drainage class	moderate	moderate	moderate	moderate	moderate	moderate	moderate	moderate
Anion storage capacity (0-100%)	30	30	30	30	30	30	50	50
P fertiliser applied (kg P ha^{-1})	20	25	40	40	30	30	30	5
Timing of P application (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)[1]	-	-	moderate	moderate	-	-	-	-
Good storage capacity for effluent	-	-	Yes/no	Yes/no	-	-	-	-
Use of artificial drainage	Yes/no	Yes/no	Yes/no	Yes/no	-	-	-	-
Wallowing[1]	-	Yes/no	-	-	-	-	-	-
Soil organic C (%)	5%	5%	5%	5%	3%	3%	5%	5%
Use of forage crops (winter; % of farm)	10	10	10	10	-	-	-	-
Use of forage crops (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	-	-	-	-	-	-

[1] See MPI (2014) and www.overseer.org.nz for fuller explanation of categorical and binary variables.
[2] not applicable.

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 to ensure that sensitive factors had good quality data. Sensitivity analyses were conducted such that outputs for numerical variables were generated by incrementally varying 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 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, 900,000 results, was analyzed to determine this size of the main effects and the 2-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/).

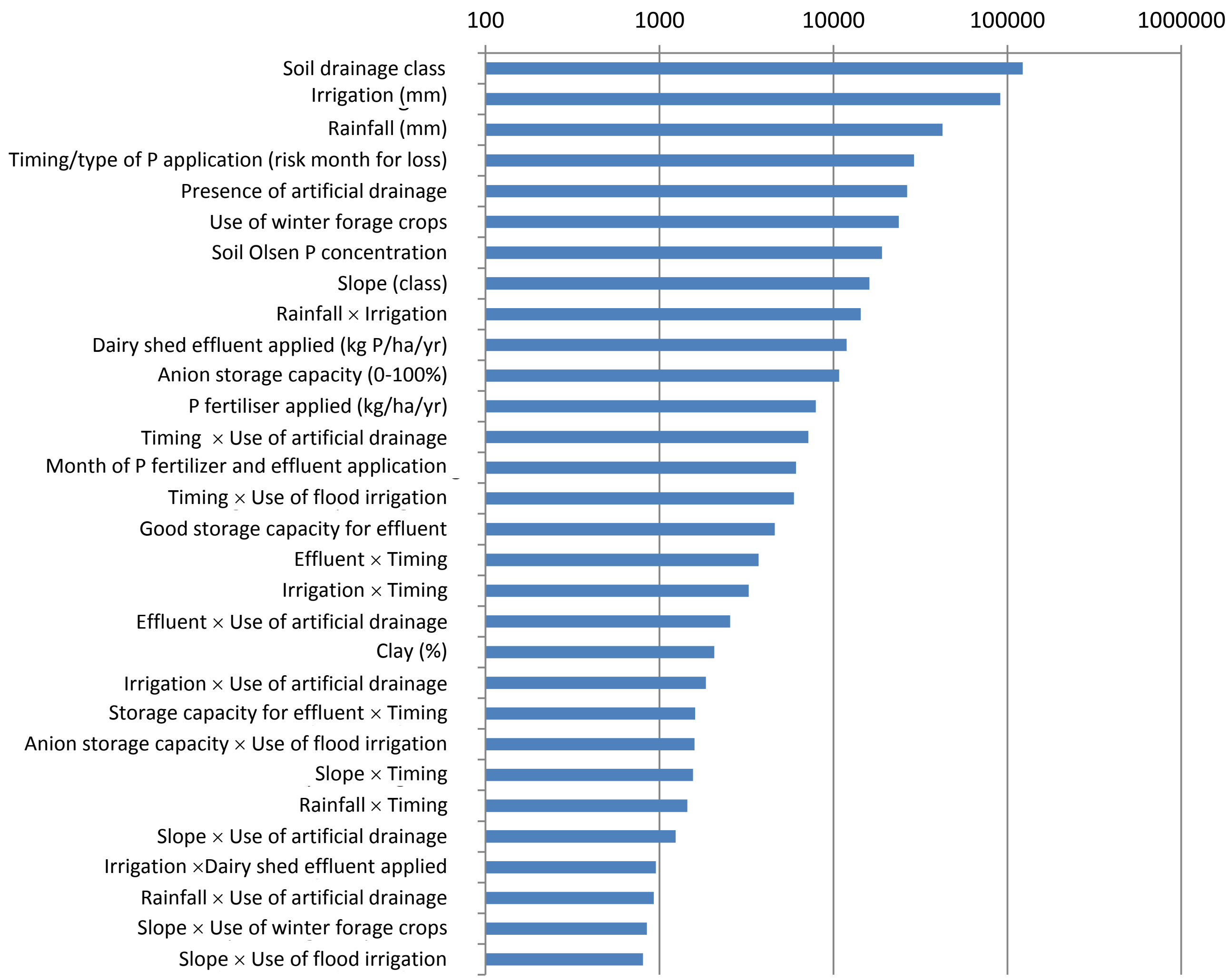


Fig. 3. Effects measured as the F ratio statistic for variation of variables in the estimation of P losses by MitAgator™; note the log scale on the axis. See McDowell et al. (2005) and MPI (2014) for an explanation of each variable.

An example output for P is given for enterprise three (an irrigated dairy farm) in Figure 3. 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; ASC) and application rates (kg P ha^{-1} y^{-1}) and types of P inputs. Hydrological variables in addition to slope all strongly influence 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 and 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 models such as CLUES (Woods et al., 2006) and SPARROW (Preston et al., 2011), which can account for in-stream attenuation down New Zealand catchment networks.

Another limitation is the temporal estimation of annual losses and mitigation performance. Both losses and performance may be subject to wide variation according to, for instance, large runoff events that account for the majority of loss but may only occur over a couple of days. Furthermore, there may be time lags in the generation of contaminant losses associated with a landuse change or in the mitigation of losses. Due to the use of Overseer algorithms, MitAgator™ assumes that both the generation of contaminant losses and effect of mitigation strategies are at steady state.

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

Conclusions

Analysis of outputs from the beta version suggest that variation in contaminant losses can be predicted (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 for P the most sensitive factors, 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 measures to assist farmers to 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).

Acknowledgements

This work was funded by Ballance Agri-Nutrients Clearview programme and the Ministry for Business, Innovation and Employment's Clean Water, Productive Land programme (C10X1006).

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