DEVELOPING N AND P EXPORT COEFFICIENTS FOR RURAL NEW ZEALAND LANDSCAPE MODELLING IN LUCI

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Introduction

Increasingly legislation and regulation require New Zealand farmers and land managers to reduce nutrient losses from their land to water. A number of models and methods are routinely used to assist with the task of identifying stocks and fluxes of nutrients in watersheds, but few offer quantification and solutions at fine spatial scale, yet are easily applied.

The Land Utilisation & Capability Indicator (LUCI) is an option in this regard. A bespoke version of LUCI is currently under development for the Ravensdown co-operative that will assist New Zealand farmers and other land managers with decision-making concerning farm ecosystems. LUCI is particularly well-suited to assessing how on-farm activities affect water quality. One aim of the collaboration is to develop algorithms that consider influential nutrient loss variables (e.g. rainfall, soil type, fertiliser use and topography) and calculate export coefficients at fine scale for use in LUCI water quality models.

This paper discusses the need for a multivariate, algorithmic approach to export coefficient calculation and demonstrates its use in the Tuapaka catchment east of Palmerston North, a largely agricultural area. Here we present results of 4 applications of LUCI water quality models to the Tuapaka catchment, each using increasingly detailed input data. These are compared to OVERSEER® predictions and in-stream nitrogen (N) and phosphorus (P) measurements.

LUCI

LUCI, an extension of the Polyscape framework described in Jackson et al. (2013a), is a GIS framework that considers impacts of land use on multiple ecosystem services in a holistic and spatially explicit manner. A number of sub-models within the framework assess ecosystem service stocks and associated indicators and processes, including water quality (total nitrogen (TN) and total phosphorus (TP)). Mass transport in LUCI is driven by unique hydrological routing algorithms which operate at the underlying digital elevation model (DEM) scale. This allows modelling of the entire range of scales, from sub-field to national, simultaneously. LUCI uses readily available national data that can be easily supplemented

with local knowledge including detailed farm management. Ecosystem service tools can be run for individual ecosystem service analysis and to analyse interrelationships between ecosystem services, identifying trade-offs and synergies among them.

LUCI water quality models use an enhanced, spatially representative export coefficient approach to model TN and TP exports to water. Within the GIS framework, annual total nutrient exports, or export coefficients (ECs), are spatially-positioned at the DEM grid-square scale and cascaded through the landscape as water and sediment accumulate and move through the catchment. For each grid-cell, both on land and in the stream network, cumulative annual nutrient load and annual average concentration is calculated. This method identifies nutrient sources and current or potential intercepting nutrient sinks. While valuable, there are issues with using the export coefficient approach.

The Export Coefficient Approach

ECs are defined as the "mass of a [contaminant] per unit area per unit time" (White et al. 2015), commonly quantified in kg ha^{-1}yr^{-1}. They are generally used in catchment scale water quality models to represent diffuse pollution associated with specific land covers and/or uses. ECs are most commonly described in association with export coefficient models (ECM), the simplest forms of which calculate the total catchment contaminant load by summing area-averaged loads from individual sources within the catchment. However, ECs are also sometimes used in more complex, mechanistic models to represent diffuse pollution from various sources (Lu et al. 2013; Shrestha et al. 2008).

Most commonly ECs sourced from literature are linked to land cover or use with minimal reference to other influential variables. However, to be representative ECs must also consider climate, soil, topography, land cover, land use and management, and scale of measurement or derivation (Grimvall and Stalnacke 1996; White et al. 2015). Clearly, many of these factors are considerably spatially varied, even at small scales. Thus, the capability to determine ECs that consider this small scale variability is important.

A multivariate, algorithmic approach to EC calculation for use in LUCI has allowed us to address small-scale variability within pastoral land covers in New Zealand. Using a large (>14 000 pastoral blocks) dataset of OVERSEER® input and output from Ravensdown, algorithms that consider climate, soil, topography, and management variables were derived using a non-linear multiple regression approach (see Jackson et al. (this issue) for further detail). LUCI water quality models use these algorithms to calculate an EC for each pastoral land cover DEM scale grid square. Currently ECs for other land covers are calculated using the same algorithms, but then scaled to respect relative differences between literature-based pasture and non-pasture land cover ECs. Development of algorithms specific to those other land cover categories would be preferred, but a lack of data hinders their derivation.

Case Study: Tuapaka Catchment

The study area is an 85ha catchment situated to the east of Palmerston North in the foothills of the Tararua Ranges (Fig. 1). Terrain is rolling to steep hill with a mix of brown and pallic soil orders. Ninety percent of the catchment is in pastoral grassland used largely for sheep and beef farming, while the remaining 10% is forested. Sixty three hectares of the catchment is within Massey University's Tuapaka Agricultural Experimental Station. Massey University have developed a detailed soil map (Pollok and McLaughlin 1986) for the experimental farm and have collected meteorological and water quality data within the catchment. Meteorological data includes rainfall and evapotranspiration from June 2013-June 2015. Ten minute flow data and monthly in-stream water quality sampling (N and P) have also been

collected for this period and a further year of monitoring is currently being undertaken. In addition, OVERSEER® has been applied to the area.

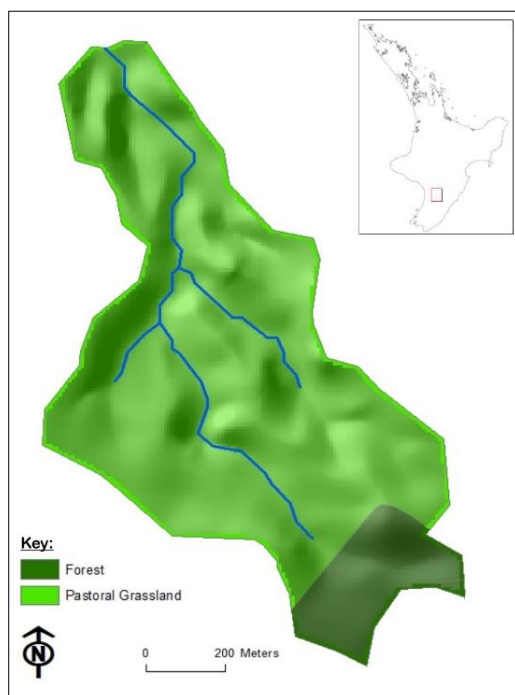

Fig. 1 - Tuapaka catchment

Comparison between actual water quality measurements taken between June 2013 and June 2014 and OVERSEER® predictions of N and P loss within this catchment were made by Burkitt et al (2016). This study builds on that work by conducting a comparative analysis between actual water quality measurements from June 2013-June 2015, OVERSEER® predictions of N and P loss, and LUCI water quality predictions. In addition, the sensitivity of LUCI's TN and TP predictions to input datasets of varying resolution and accuracy is investigated.

Method

LUCI water quality models were applied four times to the catchment using increasingly detailed and catchment specific input data with each application (Table 1). Application 1 used only the default national datasets. For Application 2, nationally available spatially varying annual average rainfall and evapotranspiration data by NIWA (Tait et al. 2006; Woods et al. 2006) was replaced by raster surfaces derived from actual rainfall and evapotranspiration data collected from June 2013-June 2014. Derivation was achieved by applying the difference between actual and modelled climate variables at the point of measurement to the NIWA raster climate surfaces. Application 3 used the above climate surfaces with the addition of the Massey University soil map for the Tuapaka Agricultural Experimental farm. This provided more spatial detail around soil variability. Application 4 used the climate surfaces based on actual data, the detailed soil data and actual farm input information from the OVERSEER® xml files. Output from the LUCI water quality models, including maps and in-stream loads, were then compared to actual water quality data and OVERSEER® predictions.

LUCI Application	Climate Data	Soil Data	Farm Input Data
Application 1	National[1]	National[2]	Regional default[3]
Application 2	Raster derived from actual rain & evap	National[2]	Regional default[3]
Application 3	Raster derived from actual rain & evap	Massey University Tuapaka Soil Map	Regional default[3]
Application 4	Raster derived from actual rain & evap	Massey University Tuapaka Soil Map[4]	Actual farm input (OVERSEER xml)

[1] Rain and evapotranspiration surfaces developed by NIWA (Tait et al. 2006; Woods et al. 2006)
[2] NZFSL
https://soils.landcareresearch.co.nz/contents/SoilData_FSL_Maps.aspx?currentPage=SoilData_FSL_Maps&menuItem=SoilData
[3] Regional farm input defaults developed by LUCI developers
[4] Pollock and McLaughlin 1986

Table 1 - Data input details between the four LUCI applications

Results and Discussion

A number of maps and data are generated by the LUCI water quality models allowing exploration of TN or TP loads and concentrations both in-stream and on land. The results are presented as a map with DEM grid cells coloured according to their total nutrient loads, from low total nutrients in red to high nutrient loads in green (Trodahl et al. In Press). Nitrogen load maps from the four applications of LUCI are shown in Fig 2a-d. While the highest and lowest TN loads remained the same for all four applications, it is clear that Application 4, with the addition of actual farm nitrogen input data for Tuapaka Agricultural Experimental farm, has lowered nitrogen loads within this area (Fig 2d).
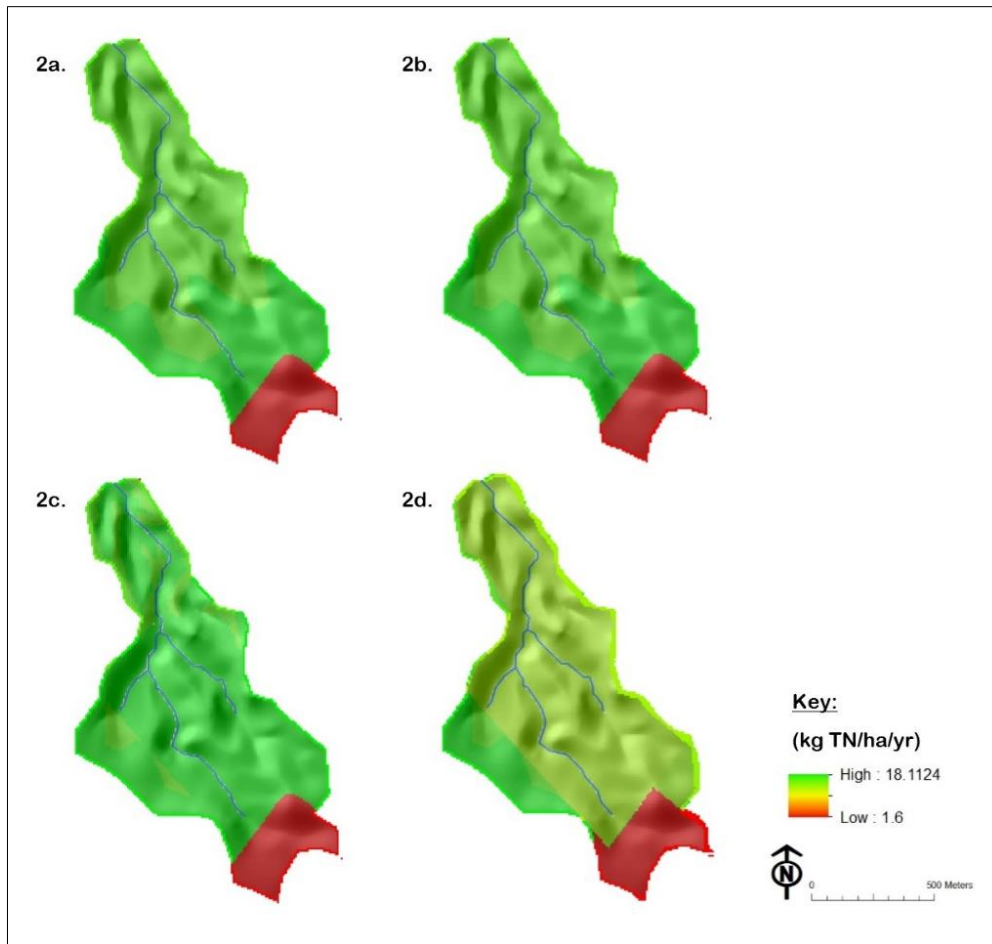

Fig 2 – Nitrogen load maps from LUCI Application 1 (2a), Application 2 (2b), Application 3 (2c) and Application 4 (2d).

Accumulated nitrogen load, classified into 3 groups, from LUCI Applications 1-4 is shown in Fig 3a-d. These indicate pathways where water and nitrogen converge in the landscape. Spatially explicit identification of these pathways illustrate where opportunities exist to intercept nutrients before they enter the stream network. Like Fig 2, maps from Applications 1-3 are very similar. Fig 3d, however, more clearly identifies pathways of very high load allowing more specific spatial targeting of areas for interventions and mitigations.
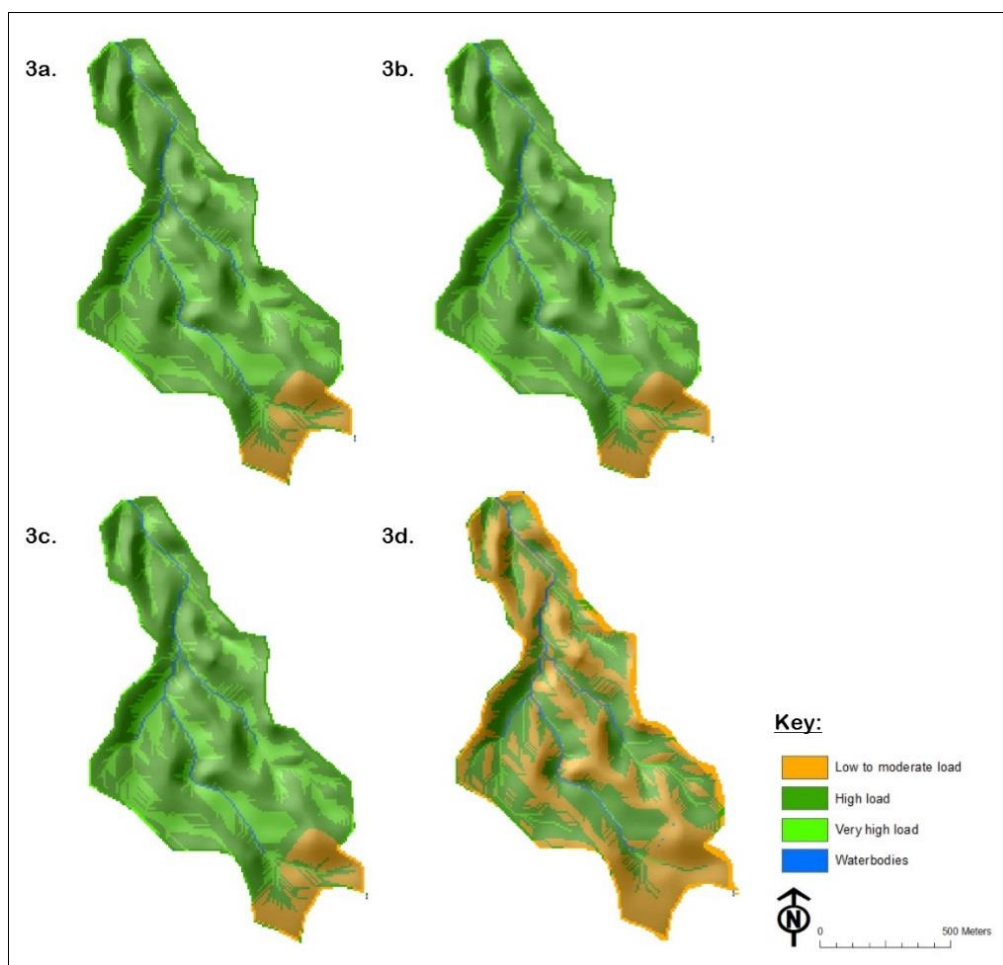
Fig 3 – Accumulated nitrogen load maps from LUCI Application 1 (3a), Application 2 (3b), Application 3 (3c) and Application 4 (3d).

Fig 4 shows P load maps from Applications 1-4. Figs 4a and 4b are very similar with the highest P loads sourced from the steeper pastoral grassland and lowest loads from the forested area and flatter pastoral grassland in the upper catchment. With the addition of the detailed soil map in Application 3 (Fig 4c), the highest P loads reduced to 8.8kg TP/ha/yr from 12.3kg TP/ha/yr in Applications 1 & 2. This is because the Massey University soil map indicates low P retention pallic soils only make up 20% of the catchment compared to 80% with the national soil map. A further reduction in the highest P loads (to 5.6kg TP/ha/yr) is seen with the addition of actual farm inputs in Application 4 (Fig 4d).

Classified accumulated P load maps from LUCI Applications 1-4 are shown in Fig 5a-d. Like Fig 3, these show pathways of water and P convergence in the landscape where opportunities exist to intercept nutrients before they enter the stream network. As with N, it is clear the addition of actual, more detailed data better defines pathways, allowing for more specific spatial targeting of interventions and mitigations.

Table 2 summarises N and P specific load from measured water quality data, OVERSEER®, and the four LUCI applications. Average specific load, based on measurements from June 2013-June 2015, is shown in row 1 with the range over the two years in brackets. OVERSEER® estimates of N and P annual average loses are shown in row 2, and below that, predictions of N and P specific load for each of the four LUCI applications.
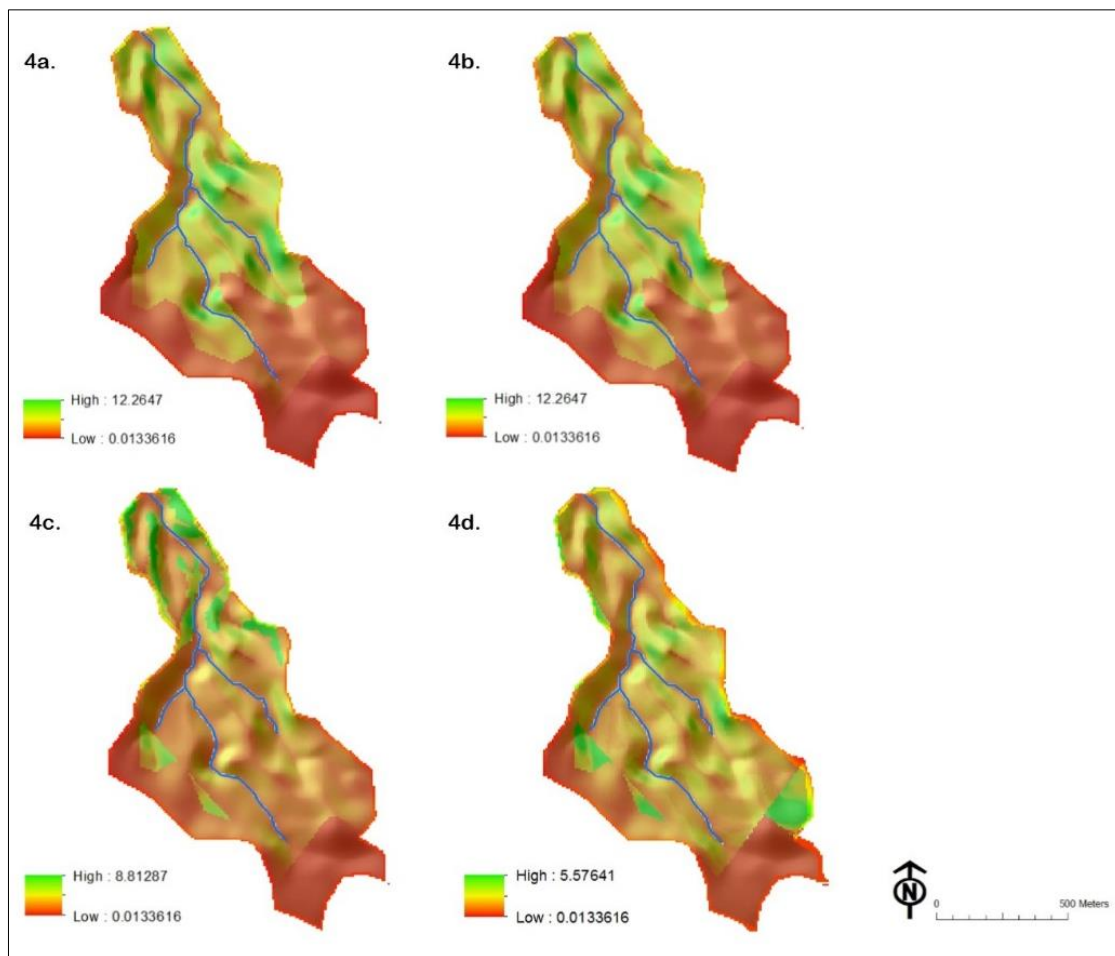
Fig 4 –Phosphorus load maps from LUCI Application 1 (4a), Application 2 (4b), Application 3 (4c) and Application 4 (4d).

It is clear from the maps and Table 2 that there is little difference between the outcomes from LUCI Application 1 and Application 2. The rainfall and evapotranspiration data from Massey University indicated a difference of 10% compared to annual average rainfall and evapotranspiration for the area from the NIWA data. In terms of excess rainfall (ie. rainfall less evapotranspiration) the difference between the measured and modelled data was only 7%. Clearly these differences were not sufficient to significantly change LUCI output for N or P. The addition of detailed soil data in Application 3 had a clear impact on sources and loads of P due to significant decreases of pallic soil within the catchment. Detailed farm input data also decreased loads for both N and P. These differences indicate that using data specific to a catchment or farm is preferable for use in LUCI, where it is available. Additionally, this highlights the ease with which actual and specific data can be incorporated for use in LUCI.

Clearly there are differences between LUCI predictions and measured specific loads (Table 2). While uncertainties exist around water quality measurements, particularly for P at the monthly sampling scale (Johnes 2007; Krueger et al. 2012; Lloyd et al. 2016), this analysis suggests that further development to improve representation of nutrient attenuation in the catchment may improve the accuracy of LUCI predictions. Currently two catchment scale attenuation factors lump into one linear coefficient the impact of losses, lags and/or transformations from root zone to stream, and a similar factor represents within-stream attenuation. However, attenuation variability at the scales within which LUCI operates could be better represented.
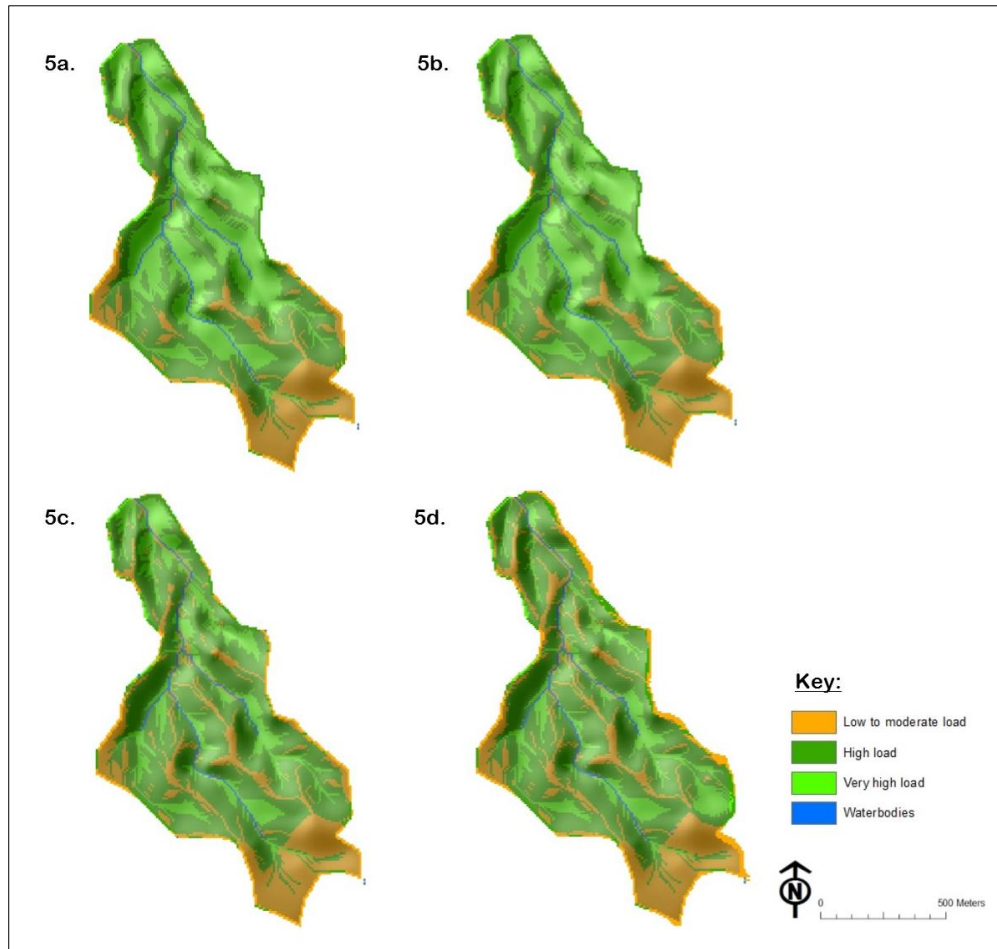
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Fig 5 –Nitrogen Load maps from LUCI Application 1 (5a), Application 2 (5b), Application 3 (5c) and Application 4 (5d).

Model/Measured	NITROGEN Specific Load (kg N/ha/yr)	PHOSPHORUS Specific Load (kg P/ha/yr)
Measured	2.37 (1.67-3.07)	0.12 (0.06-0.18)
Overseer	8	0.8
LUCI Application 1	7.39	0.77
LUCI Application 2	7.39	0.77
LUCI Application 3	7.7	0.33
LUCI Application 4	6.23	0.28

Table 2 – Measured and modelled specific load for the Tuapaka catchment. Note for Row 1 mean is presented with range in brackets.

Conclusion

Development of a novel multivariate, algorithmic approach to EC calculation has allowed us to address small-scale variability within pastoral land covers, enhancing farm to catchment scale water quality modelling in LUCI. Exploration of the effect of data resolution and detail on TN and TP exports using this newly developed method in the Tuapaka catchment

indicates that using data specific to a catchment or farm is preferable for use in LUCI, where it is available.

However, clear differences still exist between measured nutrient losses and LUCI predictions at the catchment scale. Improved understanding and subsequent better representation of nutrient attenuation in the catchment is likely to improve the accuracy of LUCI predictions. Currently, attenuation is broadly accounted for in LUCI with catchment wide root zone to stream and in-stream attenuation factors applied for N and P respectively. Development of attenuation factors that account for small scale spatial variability within catchments and recognise different processes (lag times, biogeochemical transformations, etc.) is desired. This, in addition to development of EC algorithms for other land cover types, are areas for further investigation.

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