



# Upscaling NZ-DNDC using a regression based meta-model to estimate direct N<sub>2</sub>O emissions from New Zealand grazed pastures



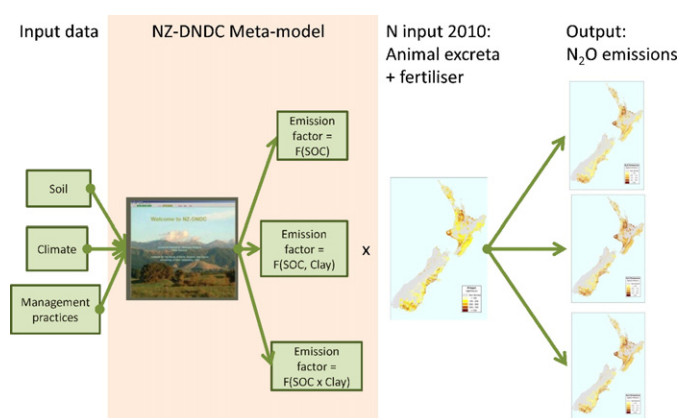
Donna L. Giltrap<sup>\*</sup>, Anne-Gaëlle E. Ausseil

Landcare Research, Palmerston North, New Zealand

## HIGHLIGHTS

- Simplified meta-models of NZ-DNDC for N<sub>2</sub>O emission factors were generated.
- Soil carbon and clay content were found to be important factors.
- National N<sub>2</sub>O emissions were calculated using these meta-models.
- Uncertainties depended upon assumptions about the spatial correlation of model errors.

## GRAPHICAL ABSTRACT



## ARTICLE INFO

### Article history:

Received 18 June 2015

Received in revised form 30 July 2015

Accepted 18 August 2015

Available online 9 September 2015

Editor: D. Barcelo

### Keywords:

NZ-DNDC

Nitrous oxide

Meta-model

Regional scale

## ABSTRACT

The availability of detailed input data frequently limits the application of process-based models at large scale. In this study, we produced simplified meta-models of the simulated nitrous oxide (N<sub>2</sub>O) emission factors (EF) using NZ-DNDC. Monte Carlo simulations were performed and the results investigated using multiple regression analysis to produce simplified meta-models of EF. These meta-models were then used to estimate direct N<sub>2</sub>O emissions from grazed pastures in New Zealand.

New Zealand EF maps were generated using the meta-models with data from national scale soil maps. Direct emissions of N<sub>2</sub>O from grazed pasture were calculated by multiplying the EF map with a nitrogen (N) input map. Three meta-models were considered. Model 1 included only the soil organic carbon in the top 30 cm (SOC30), Model 2 also included a clay content factor, and Model 3 added the interaction between SOC30 and clay. The median annual national direct N<sub>2</sub>O emissions from grazed pastures estimated using each model (assuming model errors were purely random) were: 9.6 Gg N (Model 1), 13.6 Gg N (Model 2), and 11.9 Gg N (Model 3). These values corresponded to an average EF of 0.53%, 0.75% and 0.63% respectively, while the corresponding average EF using New Zealand national inventory values was 0.67%. If the model error can be assumed to be independent for each pixel then the 95% confidence interval for the N<sub>2</sub>O emissions was of the order of  $\pm 0.4$ –0.7%, which is much lower than existing methods. However, spatial correlations in the model errors could invalidate

<sup>\*</sup> Corresponding author at: Private Bag 11052, Manawatu Mail Centre, Palmerston North 4442, New Zealand.

E-mail address: [giltrapd@landcareresearch.co.nz](mailto:giltrapd@landcareresearch.co.nz) (D.L. Giltrap).

this assumption. Under the extreme assumption that the model error for each pixel was identical the 95% confidence interval was approximately  $\pm 100$ –200%. Therefore further work is needed to assess the degree of spatial correlation in the model errors.

© 2015 Elsevier B.V. All rights reserved.

## 1. Introduction

In New Zealand, N<sub>2</sub>O emissions from agricultural soils are a major greenhouse gas source, accounting for 10.4% of emissions on a CO<sub>2</sub> equivalent (CO<sub>2</sub>e) basis (Ministry for the Environment, 2015). These emissions result from the microbial transformation of N-containing compounds in animal excreta and fertilisers applied to soils. As there are a large number of interacting processes involved in the production of N<sub>2</sub>O, emission rates are highly variable and can be influenced by many soil, management and climate factors. N<sub>2</sub>O emissions can be either direct (N<sub>2</sub>O emitted from the point of application) or indirect (emissions occurring offsite from leached NO<sub>3</sub><sup>−</sup> or volatilised and redeposited NH<sub>3</sub>). In this study we consider only direct N<sub>2</sub>O emissions from grazing animal excreta and fertiliser N, although similar methods could be used to model the NO<sub>3</sub><sup>−</sup> leaching and NH<sub>3</sub> volatilisation.

New Zealand currently uses a Tier II approach to calculate N<sub>2</sub>O emissions in the National Inventory (Ministry for the Environment, 2015). This involves multiplying the total amount of N from fertiliser and animal excreta applied to soil by country specific emission factors (EFs). These EFs are 0.01 for urine, 0.0048 for urea, and 0.0025 for faecal N. Lower EFs are used for the fractions of excretal and fertiliser N that are applied with a nitrification inhibitor. The inventory model has the advantage of being simple to apply and the required activity data are available at national scale. However, using this Tier II methodology the N<sub>2</sub>O emissions are not sensitive to changes in weather conditions, soil types or management strategies (other than DCD application or an overall reduction in animal excreta or fertiliser applications). This method also results in a high uncertainty in the estimated N<sub>2</sub>O emissions. Kelliher et al. (2003) estimated that for the 2002 inventory the relative error of total N<sub>2</sub>O emissions ranged from −42% to +74% (95% confidence interval), of which 88% was attributed to uncertainty in the value of EF for animal excreta.

Process-based models are an alternative approach to estimating N<sub>2</sub>O emissions. These models aim to simulate the underlying processes that result in N<sub>2</sub>O emissions. This means that not only are the models sensitive to changes in soil, climate or management factors, there is also the potential to simulate multiple impacts simultaneously (e.g. N<sub>2</sub>O emissions, NO<sub>3</sub><sup>−</sup> leaching, crop growth). There are a number of process-based models that can simulate N<sub>2</sub>O emissions, with DNDC (Li et al., 1992) and DayCENT (Parton et al., 1996) being two of the most widely used.

In this study we focus on the DNDC (DeNitrification DeComposition) model. DNDC is a process-based model that consists of a number of interacting sub-modules that simulate the soil thermal-hydraulic processes, plant growth, decomposition, nitrification, and denitrification (Li et al., 1992). The soil is divided into a number of uniform horizontal layers and the model simulates transport of water and nutrients in 1 dimension only. The model operates on a daily time-step, but uses an hourly time-step for the nitrification/denitrification processes. The model uses daily climate input data and can simulate a range of different crops and management practices. Since its initial development there have been many modifications and improvements to the model (reviewed by Gilhespy et al., 2014; Giltrap et al., 2010). NZ-DNDC is a New Zealand specific version of the DNDC model that has been adapted to New Zealand's year-round grazed pasture systems (Saggar et al., 2004, 2007a) and validated against N<sub>2</sub>O data for dairy- (Saggar et al., 2004) and sheep- (Saggar et al., 2007b) grazed systems. NZ-DNDC was based on DNDC version 8.6 K. Further developments have been made to the DNDC model and these have not all been captured in NZ-DNDC.

DNDC has been applied at regional or higher scale for a number of different outputs, farms systems, and countries (e.g. Butterbach-Bahl et al., 2004, 2009; Follador et al., 2011; Fumoto et al., 2010; Giltrap et al., 2008; Kesik et al., 2005; Kiese et al., 2008; Leip et al., 2011b; Levy et al., 2007; Li et al., 2004, 2014; Liu et al., 2006; Lugato et al., 2010; Miehle et al., 2006; Pathak et al., 2005; Qiu et al., 2011; Sleutel et al., 2006; Smith et al., 2004; Tang et al., 2006, 2010; Werner et al., 2007; Xu et al., 2011, 2012; Zhang et al., 2006, 2009a,b, 2010, 2011, 2012). The method involves dividing the region into a number of smaller units for which the input parameters are assumed to be homogeneous and running the model for each sub-unit. However, there are some limitations with this method. Obtaining the full set of input data for each sub-unit is usually not possible, requiring some assumptions to be made. The assumption of homogeneous sub-units will also cause some uncertainties, although these can be quantified if information about the distribution of the input parameter within a sub-unit is available. Lack of suitable data for model validation is also a common limitation (Leip et al., 2011a). In addition, the computer run-time required may be high when there are a large number of sub-units to simulate, and it is not always easy to integrate the full process-based model with other models (e.g. economic models, decision support tools). The uncertainty is estimated using the most sensitive factor (MSF) method, where each sub-unit is run using the minimum and maximum value of the MSF to estimate the possible range of the emissions.

Meta-modelling is a method for producing a simplified version of a model that preserves the key relationships between the input variables and the response (within the domain of interest) but with lower computational and/or data requirements. To develop a meta-model the full model is run many times over the full range of possible data inputs. The meta-model is then developed using statistical methods on the model inputs and output. It should be noted that the meta-model will only be a valid representation of the full model over the range of input values originally simulated and should not be used for extrapolation.

Several studies have used meta-modelling techniques on the DNDC model. Britz and Leip (2009) developed meta-models of DNDC for 13 output variables with 11 crops in Europe. Each meta-model was a regression model. There were just under 200 parameters offered for selection for each model (including transformations and interactions of the basic inputs) and each meta-model typically included between 50 and 100 regressors.

Villa-Vialaneix et al. (2012) used multiple methods to generate meta-models of DNDC for N<sub>2</sub>O emissions from arable land in Europe. These methods included linear regression models, splines, kriging, a neural network, support vector machine (SVM), and a random forest. They found that the splines method worked best when there were few training data available, but for large training data sets the SVM and random forest method produced faster and more accurate results. Perlman et al. (2014) estimated global N<sub>2</sub>O emissions from wheat and maize using a random forest meta-model of DNDC.

The New Zealand specific version of DNDC (NZ-DNDC; Saggar et al., 2004, 2007a) has been used directly to estimate N<sub>2</sub>O emissions from agriculture in the Manawatu-Wanganui region (Giltrap et al., 2008). Giltrap et al. (2013) also developed an emission factor look-up table for N<sub>2</sub>O emissions from grazed pastures based on climate region, soil and farm type based on large number of simulations covering the range of soil and climate inputs. However, this method still produced large uncertainties due to the soil categories used having very broad ranges for key properties.

Download English Version:

<https://daneshyari.com/en/article/6325007>

Download Persian Version:

<https://daneshyari.com/article/6325007>

[Daneshyari.com](https://daneshyari.com)