Contents lists available at ScienceDirect

# Applied Soil Ecology

journal homepage: www.elsevier.com/locate/apsoil

## Mineralizable nitrogen and denitrification enzyme activity drive nitrate concentrations in well-drained stony subsoil under lucerne (Medicago sativa L.)

Jonathan Nuñez<sup>a,b,\*</sup>, Kate H. Orwin<sup>a</sup>, Gabriel Y.K. Moinet<sup>a,1</sup>, Scott L. Graham<sup>a</sup>, Graeme N.D. Rogers<sup>a</sup>, Matthew H. Turnbull<sup>b</sup>, Timothy J. Clough<sup>c</sup>, Andrew Dopheide<sup>d</sup>, Carina Davis<sup>a</sup>, Gwen-Aëlle Grelet<sup>a</sup>, David Whitehead<sup>a</sup>

<sup>a</sup> Manaaki Whenua – Landcare Research, PO Box 69040, Lincoln 7640, New Zealand

<sup>b</sup> School of Biological Sciences, University of Canterbury, Private Bag 4800, Christchurch, New Zealand

<sup>c</sup> Department of Soil and Physical Sciences, PO Box 85084, Lincoln University, Lincoln 7647, New Zealand

<sup>d</sup> Manaaki Whenua – Landcare Research, Private Bag 92170, Auckland Mail Centre, Auckland 1142, New Zealand

ARTICLE INFO

Keywords: Alfalfa Microbial communities Nitrification Nitrogen mineralization Structural equation modelling Nitrate leaching

ABSTRACT

Nitrogen (N) inputs to agricultural systems contribute substantially to soil nitrate ( $NO_3^-$ ) concentrations, which increase NO<sub>3</sub><sup>-</sup> leaching and contamination of groundwater. The influence of soil microbes in regulating NO<sub>3</sub><sup>-</sup> concentrations in the topsoil are well studied but it is often assumed that microbial regulation of  $NO_3^-$  concentrations in the subsoil is negligible. The aim of this study was to test this assumption by determining the relationships between microbial properties and  $NO_3^-$  concentrations in both the subsoil and the topsoil. We measured the size of the mineralizable N  $(N_m)$  pool, microbial properties (microbial biomass, bacterial richness), nitrifier gene abundance (amoA gene copy number), denitrifier gene abundance (nirK and nirS gene copy number), denitrifier enzyme activity and  $NO_3^-$  concentrations in the topsoil and the subsoil in a well-drained stony soil under an established lucerne crop. We used structural equation modelling (SEM) to identify and compare the linkages of microbial properties with  $NO_3^-$  concentrations at each depth. In the topsoil, we found higher N<sub>m</sub>, gene abundance, denitrification enzyme activity, bacterial richness, and microbial biomass than those in the subsoil, but there were no relationships between these variables and  $NO_3^-$  concentrations in the topsoil (the SEM model explained 0.06% of the variability in  $NO_3^-$  concentrations). In contrast, in the subsoil,  $NO_3^$ concentrations were strongly correlated with bacterial amoA abundance and denitrification enzyme activity, with both variables associated significantly with  $N_{\rm m}$ . We found that bacterial richness was also associated with  $N_{\rm m}$  in the subsoil. Our findings highlight that microbial properties are associated with NO<sub>3</sub><sup>-</sup> concentrations in the subsoil (the SEM model explained 82% the variability in  $NO_3^-$  concentrations) and this suggest that nitrification and denitrification may contribute to regulating  $NO_3^-$  concentrations in the subsoil. Our findings also suggest that denitrification contributes to reducing  $NO_3^-$  concentrations in the subsoil. We conclude that studies addressing drivers of NO<sub>3</sub><sup>-</sup> leaching need to consider the potential for microbially-mediated attenuation (or an increase) in NO3<sup>-</sup> concentrations throughout the soil profile.

## 1. Introduction

Soil nitrate  $(NO_3^{-})$  can be leached from soil, potentially resulting in the contamination of groundwater (Galloway et al., 2008; Lassaletta et al., 2014). This is of particular concern in agricultural systems on well-drained soils, where inputs of urea fertiliser, ruminant excreta, and N-fixing crops contribute to high nitrogen (N) inputs to the soil (Cameron et al., 2013; Carrick et al., 2013). The amount of N that contributes to soil NO<sub>3</sub><sup>-</sup> concentrations is regulated mainly by two microbial processes comprising conversion of ammonium  $(NH_4^+)$  to  $NO_3^$ via nitrification, and denitrification of NO<sub>3</sub><sup>-</sup> into various N gases, with both processes being regulated by the mineralization of organic N

\* Corresponding author at: ETH Zurich - Department of Environmental Systems Science, Universitätstrasse 16, 8092 Zürich, Switzerland. E-mail address: jonathan.nunez@usys.ethz.ch (J. Nuñez).

https://doi.org/10.1016/j.apsoil.2022.104499

Received 13 September 2021; Received in revised form 9 March 2022; Accepted 4 April 2022 Available online 13 April 2022

0929-1393/© 2022 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).





<sup>&</sup>lt;sup>1</sup> Present address: Soil Biology Group, Wageningen University and Research, PO Box 47, 6700 AA, Wageningen, The Netherlands.

(Cameron et al., 2013; Saggar et al., 2013). These processes are well studied in the topsoil (0–0.3 m depth) but the contribution of microbial processes to  $NO_3^-$  concentrations in the subsoil (>0.3 m depth) is less well studied and is often assumed to be insignificant (Cameron et al., 2013; Hansen et al., 2019). However, there can be substantial N reserves at lower depths (Rumpel and Kögel-Knabner, 2011) and accumulation of  $NO_3^-$  through the soil profile in agricultural soils (Ju et al., 2004). This suggests that mineralization of organic N, nitrification and denitrification could contribute significantly to regulating  $NO_3^-$  concentrations in the subsoil and leaching losses (Jahangir et al., 2012).

Variations in subsoil  $NO_3^-$  concentrations are attributed primarily to leaching from topsoil (Habteselassie et al., 2006; Trolove et al., 2019). However, in the subsoil where root biomass and N uptake are low, the contribution of microbial processes to regulating  $NO_3^-$  concentrations may be higher than the contribution in the topsoil. Despite decreases in substrate availability with depth (Spohn et al., 2016) that may contribute to differentiation in the microbial abundance of nitrifiers and denitrifiers genes (Li et al., 2018; Wang et al., 2017) and microbial adaptations to overcome N limitations (Tian et al., 2017).

The size of the mineralizable N ( $N_{\rm m}$ ) pool is a driver for carbon (C) and N availability in the topsoil (Curtin et al., 2012; Mooshammer et al., 2014) and may also play a key role in regulating C and N availability for microbes in the subsoil. Mineralization of organic N is linked to microbial biomass (Mikha et al., 2005; Li et al., 2019), soil water content and temperature (Li et al., 2019). The effects of these variables on nitrification and denitrification and consequently NO3<sup>-</sup> concentrations are not well known for subsoil. Furthermore, soil microbial community composition may change in relation to the availability of substrates (Tardy et al., 2015), so microbial community properties (e.g., bacterial richness) can be expected to be linked to resources (i.e., Nm), particularly in the nutrient depleted conditions in the subsoil (Dopheide et al., 2021). Determining the direction and magnitude of the contribution of  $N_{\rm m}$  to NO<sub>3</sub><sup>-</sup> concentrations and its relationship to bacterial richness and microbial biomass in the subsoil is needed to identify management practices that will reduce NO3<sup>-</sup> concentrations and risks of leaching in well-drained agricultural systems.

Most studies that have attempted to describe nitrification and denitrification in the subsoil were conducted in the laboratory under controlled conditions. Artificially increasing the availability of C and  $NO_3^-$  to subsoil in incubation experiments increased the potential for denitrification with samples collected at depths to 1 m (Clough et al., 1998) and >6 m (Yeomans et al., 1992). These observations suggest that, in field conditions, the potential for microbial reduction of  $NO_3^$ concentrations may be linked to factors that influence C and N availability.

In this study, our objective was to identify differences in the role of soil microbes in regulating NO<sub>3</sub><sup>-</sup> concentrations in the topsoil and the subsoil in field conditions. We selected a single location where lucerne had been grown for two years on a well-drained, stony soil. The two depths for our measurements (topsoil 0-0.1 m and subsoil 0.3-0.5 m) were selected because of contrasting soil environments and root density (Sim et al., 2015). We investigated the extent to which  $N_{\rm m}$  was related to NO3<sup>-</sup> concentration and the relationship of this substrate pool with nitrifier and denitrifier gene abundance and denitrification enzyme activity. To provide further evidence of the role  $N_{\rm m}$  as an indicator of substrate availability in nutrient depleted conditions, we also determined linkages between  $N_{\rm m}$ , microbial biomass and bacterial richness. To interpret the multiple factors affecting NO<sub>3</sub><sup>-</sup> concentrations we used structural equation modelling (SEM), which provides a framework to test for the significance of multiple variables driving N transformations (Porre et al., 2016; Feng et al., 2019; Li et al., 2019). We used SEM to distinguish the relationships between the different microbial properties and soil  $NO_3^-$  concentrations. We hypothesized that (1) relationships between NO<sub>3</sub><sup>-</sup> concentrations, microbial properties and N<sub>m</sub> are stronger in the subsoil compared to those in the topsoil, and (2) denitrification

enzyme activity and denitrifier gene abundance are positively associated with  $N_{\rm m}$  in the subsoil in field conditions, consistent with observations from incubation studies with artificial increases in substrate availability (Yeomans et al., 1992; Clough et al., 1998; Jahangir et al., 2012).

## 2. Materials and methods

#### 2.1. Site characteristics and soil sampling

The experimental site was located at the Ashley Dene Research and Development Station, Lincoln, New Zealand (latitude 43° 38.85′ S longitude 172° 20.76′ E, elevation 17 m above sea level). The soil is stony, well drained and classified as a Pallic Firm Brown (FB) (New Zealand classification), Haplic Cambisol (World Reference Base) (Hewitt et al., 2021). Two years after lucerne (Alfalfa, *Medicago sativa* L.) was established, soil monoliths were extracted in autumn (late May) when seasonal plant growth had almost ceased from two adjacent paddocks which were managed for cut-and-carry fodder with no grazing. One paddock received no inputs, and the other was irrigated with water and dairy effluent up to one month prior to sampling. Further details of the characteristics of the field site and irrigation with water and dairy effluent are reported in Laubach et al. (2019) and Graham et al. (2022).

Within a  $12 \times 30$  m rectangular zone in each paddock, six sampling lanes 1.1 m wide and 28 m long were marked, with a 0.55 m buffer zone between each lane, and a 1 m buffer zone around the edge. One sampling point was generated randomly within each lane for the extraction of a soil monolith and the sampling points within each paddock were at least 2.2 m distant from each other. Each soil monolith (32 in total) was extracted by driving a steel tube (0.2 m diameter  $\times$  1.7 m length) with a PVC liner vertically into the ground using a commercial drilling rig. This sampling regime was designed to incorporate natural variability to test the role of microbial processes in regulating soil NO<sub>3</sub><sup>-</sup> concentrations for the same soil type and environmental conditions.

We collected soil samples for both the topsoil (0–0.1 m) and the subsoil (0.3–0.5 m) with depths selected because of a clear decrease in lucerne root biomass with increasing depth (Sim et al., 2015) and this was confirmed qualitatively during the sampling. All field and laboratory equipment and collection procedures were undertaken under sterilised conditions to avoid cross contamination between samples. The soil samples were homogenised, and all visible roots and stones were removed prior to subsampling for chemical and biological analyses. Subsamples for molecular analyses were frozen immediately in liquid nitrogen and stored at -80 °C until further processing. Subsamples for soil enzymatic assays and chemical analyses were stored at 4 °C for 1 week prior to analysis.

## 2.2. Measurements of soil properties

To provide context for differences in the soil properties at the two depths, pH and gravimetric water content ( $W_g$ ) were measured. Soil pH was measured in soil extracts in distilled water (2 soil:5 water mass/volume), and  $W_g$  was calculated from the difference in mass between the fresh and oven-dried (105 °C for 24 h) samples.

The concentrations of total soil carbon ( $C_{total}$ ) and nitrogen ( $N_{total}$ ) in the soil organic matter (SOM) were measured using a CN analyzer (LECO Corporation, St. Joseph, Michigan, USA). The size of the mineralizable N ( $N_m$ ) pool was estimated using the standard anaerobic method. Briefly, 10 g of soil was incubated in sealed containers with minimal headspace in anaerobic conditions (fully immersed in water) for 7 days at 40 °C. The difference in ammonium (NH<sub>4</sub><sup>+</sup>-N) concentrations before and after incubation for 7 days was assumed to be the N fraction from SOM that is mineralizable (Keeney and Bremner, 1996). The substrate availability for nitrification was estimated from soil NH<sub>4</sub><sup>+</sup>-N concentration. Soil NH<sub>4</sub><sup>+</sup>-N and NO<sub>3</sub><sup>-</sup>-N concentrations were measured in extracts with 2 M KCl and a soil:solute ratio of 1:10 mass/volume, using a QuikChem 8500 flow injection analyzer (Lachat Instruments, Loveland, CO, USA).

## 2.3. Denitrification enzyme activity

Denitrification enzyme activity  $(D_e)$  was used as a comparative estimate of the amount of active denitrification enzymes among samples, measured following Chirinda et al. (2011). To determine the activity of actual denitrifier enzymes, while preventing the synthesis of new enzymes (Tiedje, 1994), measurements of N<sub>2</sub>O production from soil were made after a short incubation period (6 h) following the application of chloramphenicol (1 g l<sup>-1</sup>). Briefly, a sample of 10 g of equivalent dry soil was incubated with a 25 ml solution containing KNO3 (1 mM) and glucose (1 mM), as N and C substrates for denitrification. The soil and solution were placed in a 100 ml hermetically sealed jar with a septum in the lid. Anaerobic conditions were applied by evacuating and flushing the jar three times with helium. Using a syringe, 10 ml of headspace air was removed and replaced with 10 ml of acetylene gas to prevent reduction (full denitrification) of N2O to N2. Three replicates for each soil sample were incubated on a rotary shaker at 25 °C and gas samples were removed after 0, 2, 4 and 6 h. N<sub>2</sub>O concentrations in the gas samples were measured on a gas chromatograph (SRI-8610, SRI Instruments, Torrance, CA, USA) to determine denitrification enzyme activity from rates of N<sub>2</sub>O production.

#### 2.4. Abundance of nitrifiers and denitrifiers genes

DNA was extracted from 250 mg of frozen soil using the Nucleospin<sup>™</sup> 96 kit for soil (Macherey-Nagel, Düren, Germany) following the manufacturer's protocol, using a JANUS Automated workstation (Perkin Elmer, Waltham, Massachusetts, USA). DNA extractions were made in triplicate, and a pooled aliquot was quantified using the Quant-iT PicoGreen dsDNA Assay (Invitrogen, Carlsbad, California, USA) and diluted to a target concentration of 1 ng DNA  $\mu l^{-1}$  for qPCR reactions. The abundances of nitrifier and denitrifier genes (gene copy number) were estimated using qPCR targeting genes for nitrification (ammonia monooxygenase amoA for bacteria and archaea) and denitrification (nirS and nirK). For all genes, the qPCR mix was made with 10 µl of Sensi-FAST™ SYBR Lo-ROX mix (Bioline, Luckenwalde, Germany) and 0.5 µM for each primer in a 20 µl final volume. qPCR runs were undertaken on a MX3000P real-time PCR system (Stratagene, Agilent Technologies Inc., San Diego, California, USA). The primers for the genes are shown in Table S1. The qPCR conditions used for each gene were the same as those from previous studies reported in Table S1. All the qPCR efficiencies were greater than 90%. The gene copy abundance was calculated using the standard curve obtained from a serial dilution of plasmids containing PCR products of each specific gene, ranging from  $10^2$  to  $10^9$  gene copies  $\mu l^{-1}$ . The standard was made from a PCR product amplified from a pool of DNA collected. The PCR product was cleaned and prepared using the Pgem-T easy cloning system (Promega, Madison, WI, USA). For the qPCR of standard and samples, the melting curves were analyzed to confirm the single target fragment of the PCR products.

## 2.5. Bacterial richness and composition and microbial biomass carbon

Microbial biomass and bacterial richness were measured to characterise their relationships with  $N_{\rm m}$  and test whether these relationships are stronger in the subsoil compared to those in the topsoil (hypothesis 1). These variables together with bacterial composition also provide indicators of the differences between the microbial properties in the topsoil and the subsoil.

Microbial biomass was estimated from the amount of C contained in biomass ( $C_{\rm mb}$ ), measured following the protocol described by Sparling et al. (1990) based on the difference in extracted C between fumigated and non-fumigated samples measured using a CN analyzer.

Bacterial richness and composition were determined using a DNA metabarcoding approach. The bacterial 16s rRNA gene was amplified using the primers F515 and R806 (Caporaso et al., 2011) following the same conditions for amplification and sequencing as those reported in

## Dopheide et al. (2021).

Demultiplexed forward and reverse DNA sequences were merged and relabelled for each sample using VSEARCH (Rognes et al., 2016). Sequencing adapters and primers were trimmed from the merged sequences using cutadapt (Martin, 2011). Again, using VSEARCH, the trimmed sequences were quality filtered to remove any with >1 maximum expected error, and dereplicated to remove identical sequences. Non-singleton sequences (those represented by at least two identical sequences) were clustered into operational taxonomic units (OTUs) at a sequence identity threshold of 97% and filtered for chimeras, after which OTU abundance was inferred by mapping the trimmed sequences back to the OTU centroid sequences at a sequence identity threshold of 97%. The OTUs were assigned a taxonomic identity using the RDP Naïve Bayesian classifier (Wang et al., 2007).

Extraction blanks, and negative and positive controls, were examined for contamination. Tag jumping (Schnell et al., 2015) was accounted for by regression of contaminant abundances against the maximum of total abundances in all other samples, after which the coefficient estimates for the 90th quantile regression was used to subtract the same number of sequences from the abundances of all OTUs (Makiola et al., 2019). Bacterial richness was then determined for each sample using the R package vegan. For estimation of bacterial composition, the ordinations were estimated using Bray-Curtis distances between OTU abundances per sample converted to proportions to generate the nMDS ordination data (stress = 0.045) using the R package vegan. A PERMANOVA test showed significant differences in bacterial communities with depth. The sequences for these data were deposited in Gen-Bank Sequence Read Archive and can be accessed under BioProject PRJNA781230 (Dopheide et al., 2021).

#### 2.6. Statistical analyses

Differences in the values for the variables between depths were determined by analysis of variance (ANOVA). All statistical analyses were carried out with RStudio using R version 3.5.2 (R Development Core Team, 2018). Coefficients of variability (cv) were used as indicators of variability for each variable at each depth. Relationships between  $W_{g}$ ,  $C_{total}$  and  $N_{total}$  were tested independently for each depth with n = 32.

## 2.7. Structural equation modelling

Structural equation modelling (Lefcheck, 2016) was used to test for direct and indirect relationships between microbial properties and NO<sub>3</sub> concentrations in the topsoil and the subsoil. The statistical approach was used to test an a priori conceptual model (Fig. S1), whereby causal pathways are defined based on current knowledge of processes in soils, with the pathways arranged mathematically as a set of linear structured equations. The variables were chosen based on relationships between substrates and microbial properties, starting from total resources ( $N_{\text{total}}$ ) and followed by the pool of available substrates  $(N_m)$ , microbial properties that influence substrate supply (bacterial richness and Cmb), and direct microbial properties (gene abundance and De) associated with NO3 concentrations. pH was not included in the analysis because this did not show strong variability among the samples and between depths (Table 1). Other measured variables ( $W_g$ , bacterial composition) were used to provide further context for differences in the relationships between the topsoil and the subsoil.

In our model,  $N_{\text{total}}$  was selected as proxy for total N and C resources because  $N_{\text{total}}$  was strongly correlated with  $C_{\text{total}}$  in both the topsoil (R<sup>2</sup> = 0.97) and the subsoil (R<sup>2</sup> = 0.98). We expected that higher  $N_{\text{total}}$ would be associated with higher  $N_{\text{m}}$  and larger microbial biomass ( $C_{\text{mb}}$ ) (St. Luce et al., 2011). We also expected that higher  $N_{\text{total}}$  would be associated with greater richness because of the greater amounts of resources (Bardgett and van der Putten, 2014). Higher  $C_{\text{mb}}$  and bacterial richness were expected to be associated with a larger  $N_{\text{m}}$  and thus higher

#### Table 1

Mean ± standard deviation and the coefficient of variability for total soil carbon ( $C_{\text{total}}$ ) and nitrogen ( $N_{\text{total}}$ ) concentrations, carbon to nitrogen ratio ( $C_{\text{total}}$ : $N_{\text{total}}$ ), mineralizable nitrogen ( $N_{\rm m}$ ) pool, soil gravimetric water content ( $W_g$ ), pH, nitrate (N-NO<sub>3</sub><sup>-</sup>) and ammonium (N-NH<sub>4</sub><sup>+</sup>) concentrations, microbial biomass C ( $C_{\rm mb}$ ), bacterial richness, ammonia oxidizing bacteria (AOB *amoA*) and archaea (AOA *amoA*) gene copy number, copper containing nitrate reductase gene copy number (*nirK*), heme *c* and heme  $d_1$  containing nitrate reductase gene copy number (*nirS*), and denitrification enzyme activity ( $D_e$ ) for the topsoil and the subsoil. For all variables n = 32. The *p* values represent significance from the analyses of variance.

Variable	Topsoil		Subsoil		p value
	$\text{Mean}\pm\text{sd}$	cv (%)	$\text{Mean} \pm \text{sd}$	cv (%)	
C <sub>total</sub> (g C kg <sup>-1</sup> soil)	$51.6\pm4.8$	9	$21.8 \pm 5.9$	27	< 0.0001
N <sub>total</sub> (g N kg <sup>-1</sup> soil)	$\textbf{4.9} \pm \textbf{0.4}$	8	$1.8\pm0.5$	28	< 0.0001
$C_{\text{total}}:N_{\text{total}}$	$10.5\pm0.1$	1	$11.6\pm0.5$	4	< 0.0001
$N_{\rm m}$ (mg kg <sup>-1</sup> soil)	$100.0\pm18.7$	19	$9.32\pm6.0$	64	< 0.0001
$W_{g}(\%)$	$36.7\pm2.5$	7	$12.0\pm3.3$	28	< 0.0001
pH	$6.0\pm0.2$	3	$6.0\pm0.1$	2	0.3
N-NO <sub>3</sub> <sup>-</sup> (mg kg <sup>-1</sup> soil)	$16.8\pm6.7$	40	$1.5\pm1.4$	93	< 0.0001
N-NH4 <sup>+</sup> (mg kg <sup>-1</sup> soil)	$\textbf{2.9} \pm \textbf{4.0}$	138	$\textbf{0.9} \pm \textbf{2.4}$	267	< 0.05
$C_{\rm mb}~({\rm mg~kg^{-1}})$	658.1 $\pm$	23	119.5 $\pm$	88	< 0.0001
soil)	151.9		104.9		
Bacterial richness	3392.8 $\pm$	18	$2678.5~\pm$	13	< 0.0001
	599.5		346.3		
AOA amoA	$3.4\times10^{6}~\pm$	59	$5.3 imes10^5 ext{ }\pm$	60	< 0.0001
(copies g <sup>-1</sup> soil)	$2.0\times10^{6}$		$3.2\times10^5$		
AOB amoA	$6.9 imes10^5 \pm$	49	$4.6 imes10^4 ext{ }\pm$	113	< 0.0001
(copies g <sup>-1</sup> soil)	$3.4\times10^{5}$		$\textbf{2.2}\times 10^4$		
<i>nirS</i> (copies $g^{-1}$	$1.6 imes10^7 ext{ }\pm$	50	$2.5 imes10^{6} \pm$	74	< 0.0001
soil)	$8.0 imes10^6$		$1.9  imes 10^6$		
nirK (copies $g^{-1}$	$9.8 imes10^{6} \pm$	49	$5.3 imes10^5 ext{ }\pm$	74	< 0.0001
soil)	$4.8  imes 10^6$		$3.9  imes 10^5$		
$D_{\rm e} \ ({ m mg N-N_2O}\ { m kg^{-1} \ soil \ h^{-1}})$	$182.6\pm67.3$	37	$\textbf{7.6} \pm \textbf{5.5}$	72	< 0.0001

 $\rm NH_4^+$  and  $\rm NO_3^-$  concentrations, due to higher enzyme activity and diversity (Puri and Ashman, 1998; Tardy et al., 2015). Further, we expected that higher  $N_{\rm m}$  would supply substrate for nitrification and denitrification, and be associated with higher denitrifier enzyme activity, higher gene abundance for denitrification (*nirK*, *nirS*), and nitrification (bacterial and archaeal *amoA*). Finally, we expected that higher denitrification enzyme activity would be associated with lower  $\rm NO_3^-$  concentrations, and that a higher abundance of nitrifiers genes would be associated with higher  $\rm NO_3^-$  concentrations (Fig. S1).

We used the piecewise SEM package (Lefcheck, 2016) in R to test our conceptual model against observed data using paddock origin of samples as a random term. The goodness of fit for the model was evaluated using Shipley's test of directed separation, whereby the model was acceptable if Fisher's C was statistically non-significant (p > 0.05) (Shipley, 2009).

From initial runs of the model, we found that the archaea *amoA* gene abundance was not associated with  $N_{\rm m}$  and NH<sub>4</sub><sup>+</sup>-N concentration was not associated with  $N_{\rm m}$  or archaea *amoA* gene abundance. The model did not explain differences in either, archaea *amoA* gene abudance or NH<sub>4</sub><sup>+</sup>-N, so the model was simplified by removing these components. The denitrifying genes *nirK* and *nirS* were combined into one single variable (*nirK* + *nirS*) as they showed the same relationships in the model as those when evaluated independently (data not shown).

Standardized regression coefficients and their significance were used to indicate the strength and direction of the pathways. Conditional (all factors) coefficients of determination were reported for the models for both the topsoil and the subsoil.

#### 3. Results

## 3.1. Topsoil and subsoil physical and microbial properties

Soil  $C_{\rm total}$ ,  $N_{\rm total}$ ,  $N_{\rm m}$ ,  $W_{\rm g}$ ,  $C_{\rm mb}$ , bacterial richness, nitrifier and denitrifier gene abundances and  $D_{\rm e}$  were significantly lower in the subsoil than those in the topsoil (p < 0.0001). pH showed no significant difference between depths, with the mean  $\pm$  standard deviation being 6.0  $\pm$  0.2 (Table 1). Both NO<sub>3</sub><sup>-</sup>-N and NH<sub>4</sub><sup>+</sup>-N concentrations were significantly lower in the subsoil compared with the topsoil.

 $W_{\rm g}$  increased linearly with increasing  $C_{\rm total}$  and  $N_{\rm total}$  in the topsoil (p < 0.05) and the subsoil (p < 0.001) (Fig. 1). A higher coefficient of determination was observed for the relationship for the subsoil ( $R^2 = 0.5$ ) compared to the topsoil ( $R^2 = 0.2$ ) (Fig. 1).

Variability in total resources ( $C_{\text{total}}$  and  $N_{\text{total}}$ ), soil substrates ( $N_{\text{m}}$ ,  $\text{NO}_3^-$ -N and  $\text{NH}_4^+$ -N concentrations),  $W_{\text{g}}$ , and microbial properties (gene abundance, denitrification enzyme activity, microbial biomass C, bacterial richness) were generally higher in the topsoil compared to the subsoil (Table 1). Non-metric MDS ordinations showed very clear evidence of differences in bacterial community composition in the topsoil and the subsoil (F<sub>1</sub> = 0.63149, p < 0.001) (Fig. S2).

# 3.2. Relationships between microbial properties, mineralizable N, and $NO_3^{-}$ -N concentrations in the topsoil and the subsoil

The model explained 82% of the variation in NO<sub>3</sub><sup>-</sup>-N concentrations for the subsoil, but only 6% of the variation for the topsoil (Fig. 2). For the topsoil, there were significant relationships between  $N_{\text{total}}$  and  $N_{\text{m}}$ , and between  $N_{\text{total}}$  and  $C_{\text{mb}}$  (Fig. 2a). In the topsoil, although there were no significant relationships between the driving variables and NO<sub>3</sub><sup>-</sup>-N, there were relationships between  $C_{\text{mb}}$  and denitrifier gene abundance, denitrifier gene abundance and denitrification enzyme activity, and  $N_{\text{m}}$ and denitrification enzyme activity. The variables measured did not explain any of the variation in bacterial richness or nitrifier gene abundance in the topsoil.

The significant effects of  $N_{\text{total}}$  on  $N_{\text{m}}$  and  $C_{\text{mb}}$  in the topsoil were also detected in the subsoil (Fig. 2b). In the subsoil, there was a significant relationship between bacterial richness and  $N_{\text{m}}$ , and denitrifier gene abundance and nitrifier gene abundance, but no significant link was observed between the denitrifier gene abundance and denitrifier enzyme activity. However, NO<sub>3</sub><sup>-</sup>-N concentrations were positively associated with both  $N_{\text{m}}$  and nitrifier gene abundance, and negatively associated with denitrification enzyme activity (Fig. 2b).

## 4. Discussion

Using the natural variability in  $N_{\rm m}$  and microbial properties at the field site with the same soil type, we were able to apply the SEM model to identify the associations and quantify differences in the relationships between NO<sub>3</sub><sup>-</sup> concentrations, microbial properties, and substrate concentrations for both the topsoil and the subsoil. Our findings showed that bacterial richness and biomass, denitrifier and nitrifier gene abundance, De, and Nm were lower in the subsoil compared to the topsoil. This is consistent with observations of declining microbial biomass, gene abundance, diversity and soil resources with increasing depth for a range of ecosystems (Eilers et al., 2012; Hsiao et al., 2018; Stone et al., 2014). The contrasting environments in the topsoil and the subsoil hosted bacterial communities with different composition, consistent with previous reports suggesting that decreasing substrate availability associated with depth is the main driver for differences in community composition (Zhang et al., 2017; Dopheide et al., 2021). The fact that a significant relationship was observed between richness and  $N_{\rm m}$  in the subsoil suggests that the number of bacterial species may influence the size of  $N_m$  pool, likely via increased amounts of enzymes engaged in mineralization of organic N (Tian et al., 2017; Uksa et al., 2015). Alternatively, this positive relationship may also have resulted



Fig. 1. Gravimetric soil water content (%) in relation to total nitrogen and carbon concentrations in (a, b) the topsoil (depth 0–0.1 m) and (c, d) the subsoil (depth 0.3–0.5 m). The lines shown are linear fits to the data.

from an increasing number of bacterial species with strong contribution to changes in the  $N_{\rm m}$  pool. The low density and high variability of roots (source of  $N_{\rm m}$ ) in the stony soil (Sim et al., 2015) may also have contributed to a wider variability in  $N_{\rm m}$ -rich spots in the subsoil, as reflected in the higher coefficient of variability for  $N_{\rm m}$  in the substrate compared to the topsoil. The findings further suggest that the substrate concentrations are likely to exert a selection pressure for microbes, potentially affecting the number of species (bacterial richness), in agreement with previous observations showing that microbial community composition is strongly related to the size of the substrate pool in nutrient depleted conditions in the subsoil (Dopheide et al., 2021). Future studies are needed to determine how bacterial composition relates to  $N_{\rm m}$  and how changes in composition are functionally related to mineralization of organic N in the subsoil.

Our findings suggest that  $NO_3^-$  concentrations can be strongly driven by microbial processes in a well-drained subsoil.  $NO_3^-$  concentrations in the subsoil were positively related to bacterial nitrifier abundance and negatively related to denitrification enzyme activity, with both being regulated by  $N_{\rm m}$ . Our findings confirm our second hypothesis of consistency with incubation studies showing that the

potential for denitrification and nitrification in subsoil is limited by substate availability (Clough et al., 1998; Swensen and Bakken, 1998; Chen et al., 2018). Furthermore, we provide evidence that, in conditions of low substrate availability in the subsoil, denitrification and nitrification are likely to be regulated by the supply of substrates from mineralization of organic N.

An assumption in this study is that  $N_m$  represents the potential supply of C, NH<sub>4</sub><sup>+</sup> and NO<sub>3</sub><sup>-</sup> derived from SOM through mineralization (Booth et al., 2005; Kuntz et al., 2016; Curtin et al., 2017). Despite the expected low rates of mineralization of organic N in the subsoil (Jones et al., 2018; Tian et al., 2017) the fact that two independent indicators of denitrification (gene abundance and denitrification enzyme activity) and nitrifier gene abundance were positively linked to  $N_m$  support our assumption that  $N_m$ , along with C and N supply, contribute to regulating denitrification and nitrification in the subsoil. This observation is consistent with previous reports showing that C availability (measured as water extractable C) is a strong driver for denitrification in the subsoil below the rooting zone (Jahangir et al., 2012; Chen et al., 2018; Yuan et al., 2019).

The variability in water content may also have contributed to the



Fig. 2. Structural equation modelling (SEM) to indicate relationships of soil biological and biochemical variables and substrates driving nitrate (NO<sub>3</sub><sup>-</sup>) concentrations for (a) the topsoil (depth 0-0.1 m) and (b) the subsoil (depth 0.3-0.5 m). Blue arrows indicate positive relationships and red arrows indicate negative relationships. Numbers adjacent to the arrows are standardized path coefficients (regression coefficients), with the thickness of the lines indicating the relative sizes of the coefficients. p values are shown where  $* \le 0.05$ ;  $** \le 0.01$ ; and \*\*\* < 0.001. The conditional coefficient of determination for each variable is shown in parentheses. The symbols are total soil nitrogen concentration ( $N_{\text{total}}$ ), mineralizable N ( $N_{\text{m}}$ ), microbial biomass carbon  $(C_{mb})$ , bacterial ammonia oxidizing gene copy number (amoA), nitrate reductase gene copy number (nirK + *nirS*), and denitrification enzyme activity  $(D_e)$ . Grey boxes represent substrates and green boxes represent microbial properties.

strong linkages between Nm and denitrifier gene abundance and denitrification enzyme activity. We observed a strong linear relationship between  $W_g$  and indicators of SOM ( $N_{total}$ ,  $C_{total}$ ) in the subsoil, and the model showed that  $N_{\rm m}$  was linked to  $N_{\rm total}$  contained in SOM. Increased SOM amounts could be associated with an increase in water retention (Rawls et al., 2003) and this could contribute to an increase in anaerobic conditions that promote denitrification (Clough et al., 2005). This interpretation is consistent with the lack of an expected relationship between the abundance of denitrifier genes and denitrification enzyme activity in the subsoil. The lack of a relationship between denitrifier gene abundance and denitrification enzyme activity can be explained by the variability in anaerobic conditions in the subsoil associated with variability in water content. Microorganisms harboring denitrifier genes are widespread among heterotrophic microorganisms, but their denitrification activity is triggered in anaerobic conditions (Philippot et al., 2007). We argue that in the relatively substrate depleted conditions in the subsoil compared with the topsoil, SOM hotspots supply substrates and may retain more water, providing microsite reductive conditions that enhance denitrification (Loick et al., 2017), leading to increased reduction of NO<sub>3</sub><sup>-</sup>. This suggests that water content may be a strong driver of denitrifier enzyme activity in the subsoil.

The lack of linkages between  $NO_3^-$  and soil properties was observed in the topsoil, despite the much higher  $N_m$ , microbial biomass, bacterial richness, denitrifier enzyme activity, and abundance of nitrifiers and denitrifiers compared to the subsoil. The lack of a relationship between bacterial richness and  $N_m$  in the topsoil could be explained by the higher bacterial richness that may have led to higher redundancy that decoupled richness from function compared to the subsoil (Bardgett and van der Putten, 2014; Louca et al., 2018). It is likely that frequent N inputs from agricultural management and nitrogen fixation, and N uptake associated with high root density in the topsoil (Sim et al., 2015) would have contributed to decoupling of  $NO_3^-$  concentration from  $N_m$  and indicators of nitrification and denitrification (Abalos et al., 2019), compared with low N inputs, fixation and uptake in the subsoil.

Our findings provide new insights demonstrating that, contrary to the assumption that variations in subsoil  $NO_3^-$  concentrations are driven primarily by leaching from the topsoil (Cameron et al., 2013; Hansen et al., 2019), microbially-driven processes also contribute significantly to regulating  $NO_3^-$  concentrations in the subsoil in field conditions. Consistent with previous studies suggesting the need to include depth as a factor in estimating nutrient cycling (Yost and Hartemink, 2020), our findings suggest that, to reduce uncertainties in modelling and predicting nitrate leaching losses, studies need to consider the potential for microbially-mediated attenuation (or increases) in  $NO_3^-$  concentrations throughout the soil profile.

## 5. Conclusions

We found differences in relationships between substrate availability and microbial drivers of  $NO_3^-$  concentrations in the subsoil and the topsoil under lucerne in a well-drained, stony soil. Soil NO3<sup>-</sup> concentrations in the topsoil were not related to the mineralizable N pool, nitrifier and denitrifier gene abundance or denitrification enzyme activity. In contrast, in the subsoil, NO<sub>3</sub><sup>-</sup> concentrations were related, both directly and indirectly, to these variables. Our findings suggest that microbially-driven processes contribute significantly to NO<sub>3</sub><sup>-</sup> concentrations in the subsoil. Although substrate concentrations, denitrifier gene abundance and denitrification enzyme activity in the subsoil are much lower than those in the topsoil, enhanced subsoil microbial denitrification could lead to a significant effect on reducing total NO<sub>3</sub> content because of the much larger volume of soil, and lead to reduced NO3<sup>-</sup> leaching. In well-drained subsoils, management practices to increase denitrification activity should focus on increasing the size of the mineralizable N pool and carbon availability. However, increasing subsoil denitrification may also increase N2O emissions and this needs to be considered as a trade-off effect in future field experiments.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgements

This work was undertaken as a contribution to a larger programme to develop management practices to reduce nitrogen losses from farms, with funding provided to Manaaki Whenua – Landcare Research from the Ministry of Business, Innovation and Employment Endeavour Fund, contract number C09X1610. Funding for Jonathan Nuñez was provided by a University of Canterbury Connect Scholarship and from Manaaki Whenua – Landcare Research's Strategic Science Investment Fund. We are grateful for technical help from laboratories at Lincoln University and Manaaki Whenua – Landcare Research at Palmerston North, and we thank Lincoln University and the staff at Ashley Dene Research & Development Station for access to the field site.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apsoil.2022.104499.

#### References

- Abalos, D., van Groenigen, J.W., Philippot, L., Lubbers, I.M., De Deyn, G.B., 2019. Plant trait-based approaches to improve nitrogen cycling in agroecosystems. J. Appl. Ecol. https://doi.org/10.1111/1365-2664.13489.
- Bardgett, R.D., van der Putten, W.H., 2014. Belowground biodiversity and ecosystem functioning. Nature 515, 505–511. https://doi.org/10.1038/nature13855.
- Booth, M.S., Stark, J.M., Rastetter, E., 2005. Controls on nitrogen cycling in terrestrial ecosystems: a synthetic analysis of literature data. Ecol. Monogr. 75, 139–157. https://doi.org/10.1890/04-0988.
- Cameron, K.C., Di, H.J., Moir, J.L., 2013. Nitrogen losses from the soil/plant system: a review. Ann. Appl. Biol. 162, 145–173. https://doi.org/10.1111/aab.12014.
- Caporaso, J.G., Lauber, C.L., Walters, W.A., Berg-Lyons, D., Lozupone, C.A., Turnbaugh, P.J., Fierer, N., Knight, R., 2011. Global patterns of 16S rRNA diversity at a depth of millions of sequences per sample. Proc. Natl. Acad. Sci. U. S. A. 108 (Suppl. 1), 4516–4522. https://doi.org/10.1073/pnas.1000080107.
- Carrick, S., Palmer, D., Webb, T., Scott, J., Lilburne, L., 2013. Stony soils are a major challenge for nutrient management under irrigation development. In: Currie, L.D., Christensen, C.L. (Eds.), Accurate and Efficient Use of Nutrients on Farms. Fertil. Lime Res. Centre, Massey Univ., Palmerston North, New Zealand.
- Chen, S., Wang, F., Zhang, Y., Qin, S., Wei, S., Wang, S., Hu, C., Liu, B., 2018. Organic carbon availability limiting microbial denitrification in the deep vadose zone. Environ. Microbiol. 20, 980–992. https://doi.org/10.1111/1462-2920.14027.
- Chirinda, N., Olesen, J.E., Porter, J.R., 2011. Post-cold-storage conditioning time affects soil denitrifying enzyme activity. Commun. Soil Sci. Plant Anal. 42, 2160–2167. https://doi.org/10.1080/00103624.2011.596244.
- Clough, T., Jarvis, S., Dixon, E., Stevens, R., Laughlin, R., Hatch, D., 1998. Carbon induced subsoil denitrification of 15N-labelled nitrate in 1 m deep soil columns. Soil Biol. Biochem. 31, 31–41. https://doi.org/10.1016/S0038-0717(98)00097-2.
- Clough, T.J., Sherlock, R.R., Rolston, D.E., 2005. A review of the movement and fate of N2O in the subsoil. Nutr. Cycl. Agroecosyst. 3–11 https://doi.org/10.1007/s10705-004-7349-z.
- Curtin, D., Beare, M.H., Hernandez-Ramirez, G., 2012. Temperature and moisture effects on microbial biomass and soil organic matter mineralization. Soil Sci. Soc. Am. J. 76, 2055–2067. https://doi.org/10.2136/sssaj2012.0011.
- Curtin, D., Beare, M., Lehto, K., Tregurtha, C., Qiu, W., Tregurtha, R., Peterson, P., 2017. Rapid assays to predict nitrogen mineralization capacity of agricultural soils. Soil Sci. Soc. Am. J. 81 (4), 979–991. https://doi.org/10.2136/sssaj2016.08.0265.
- Dopheide, A., Davis, C., Nuñez, J., Rogers, G., Whitehead, D., Davis, C., Rogers, G., Grelet, G.-A., 2021. Depth-structuring ofmulti-kingdom soil communities in agricultural pastures. FEMS Microbiol. Ecol. 97, 1–16. https://doi.org/10.1093/ femsec/fiab156.
- Eilers, K.G., Debenport, S., Anderson, S., Fierer, N., 2012. Digging deeper to find unique microbial communities: the strong effect of depth on the structure of bacterial and archaeal communities in soil. Soil Biol. Biochem. 50, 58–65. https://doi.org/ 10.1016/j.soilbio.2012.03.011.
- Feng, J., Penton, C.R., He, Z., Nostrand, J.D.Van, Yuan, M.M., Wu, L., Wang, C., Qin, Y., Shi, Z.J., Guo, X., Schuur, E.A.G., Luo, Y., Bracho, R., Konstantinidis, K.T., Cole, J.R., Tiedje, J.M., Yang, Y., Zhou, J., 2019. Long-term warming in Alaska enlarges the diazotrophic community in deep soils. MBio 10, 1–12. https://doi.org/10.1128/ mBio.02521-18.
- Graham, S.L., Laubach, J., Hunt, J.E., Mudge, P.L., Nuñez, J., Rogers, G.N.D., Buxton, R. P., Carrick, S., Whitehead, D., 2022. Irrigation and grazing management affect leaching losses and soil nitrogen balance of lucerne. Agric. Water Manag. 107233 https://doi.org/10.1016/j.agwat.2021.107233.
   Galloway, J.N., Townsend, A.R., Erisman, J.W., Bekunda, M., Cai, Z., Freney, J.R.,
- Galloway, J.N., Townsend, A.R., Erisman, J.W., Bekunda, M., Cai, Z., Freney, J.R., Martinelli, L.A., Seitzinger, S.P., Sutton, M.A., 2008. Transformation of the nitrogen cycle: recent trends, questions, and potential solutions. Science 320, 889–893.
- Habteselassie, M.Y., Miller, B.E., Thacker, S.G., Stark, J.M., Norton, J.M., 2006. Soil nitrogen and nutrient dynamics after repeated application of treated dairy-waste. Soil Sci. Soc. Am. J. 70, 1328. https://doi.org/10.2136/sssaj2005.0189.
- Hansen, S., Frøseth, R.B., Stenberg, M., Stalenga, J., Olesen, J.E., Krauss, M., Radzikowski, P., Doltra, J., Nadeem, S., Torp, T., Pappa, V., Watson, C.A., 2019. Reviews and syntheses: review of causes and sources of N2O emissions and NO3 leaching from organic arable crop rotations. Biogeosciences 16, 2795–2819. https:// doi.org/10.5194/bg-16-2795-2019.

- Hewitt, A.E., Balks, M.R., Lowe, D.J., 2021. The soils of Aotearoa New Zealand. In: World Soils Book Series. Springer Nature, Switzerland AG. https://doi.org/10.1007/978-3-030-64763-6.
- Hsiao, C.J., Sassenrath, G.F., Zeglin, L.H., Hettiarachchi, G.M., Rice, C.W., 2018. Vertical changes of soil microbial properties in claypan soils. Soil Biol. Biochem. 121, 154–164. https://doi.org/10.1016/j.soilbio.2018.03.012.
- Jahangir, M.M.R., Khalil, M.I., Johnston, P., Cardenas, L.M., Hatch, D.J., Butler, M., Barrett, M., O'flaherty, V., Richards, K.G., 2012. Denitrification potential in subsoils: a mechanism to reduce nitrate leaching to groundwater. Agric. Ecosyst. Environ. 147, 13–23. https://doi.org/10.1016/J.AGEE.2011.04.015.
- Jones, D.L., Magthab, E.A., Gleeson, D.B., Hill, P.W., Sánchez-Rodríguez, A.R., Roberts, P., Ge, T., Murphy, D.V., 2018. Microbial competition for nitrogen and carbon is as intense in the subsoil as in the topsoil. Soil Biol. Biochem. 117, 72–82. https://doi.org/10.1016/J.SOILBIO.2017.10.024.
- Ju, X., Liu, X., Zhang, F., Roelcke, M., 2004. Nitrogen fertilization, soil nitrate accumulation, and policy recommendations in several agricultural regions of China. Ambio 33, 300–305. https://doi.org/10.1579/0044-7447-33.6.300.
- Keeney, D., Bremner, J., 1996. Comparison and evaluation of laboratory methods of obtaining an index of soil nitrogen availability. Agron. J. 58, 498–503.
- Kuntz, M., Morley, N.J., Hallett, P.D., Watson, C., Baggs, E.M., 2016. Residue-C effects on denitrification vary with soil depth. Soil Biol. Biochem. 103, 365–375. https://doi. org/10.1016/j.soilbio.2016.09.012.
- Lassaletta, L., Billen, G., Grizzetti, B., Anglade, J., Garnier, J., 2014. 50 year trends in nitrogen use efficiency of world cropping systems: the relationship between yield and nitrogen input to cropland. Environ. Res. Lett. 9 https://doi.org/10.1088/1748-9326/9/10/105011.
- Laubach, J., Hunt, J.E., Graham, S.L., Buxton, R.P., Rogers, G.N.D., Mudge, P.L., Carrick, S., Whitehead, D., 2019. Irrigation increases forage production of newly established lucerne but enhances net ecosystem carbon losses. Sci. Total Environ. 689, 921–936. https://doi.org/10.1016/J.SCITOTENV.2019.06.407.
- Lefcheck, J.S., 2016. piecewiseSEM : piecewise structural equation modelling in r for ecology, evolution, and systematics. Methods Ecol. Evol. 7, 573–579. https://doi. org/10.1111/2041-210X.12512.
- Li, D., Zhang, X., Green, S.M., Dungait, J.A.J., Wen, X., Tang, Y., Guo, Z., Yang, Y., Sun, X., Quine, T.A., 2018. Nitrogen functional gene activity in soil profiles under progressive vegetative recovery after abandonment of agriculture at the Puding Karst Critical Zone Observatory, SW China. Soil Biol. Biochem. 125, 93–102. https:// doi.org/10.1016/J.SOIL.BIO.2018.07.004.
- Li, Z., Tian, D., Wang, B., Wang, J., Wang, S., Chen, H.Y.H., Xu, X., Wang, C., He, N., Niu, S., 2019. Microbes drive global soil nitrogen mineralization and availability. Glob. Chang. Biol. 25, 1078–1088. https://doi.org/10.1111/gcb.14557.
- Loick, N., Dixon, E., Abalos, D., Vallejo, A., Matthews, P., McGeough, K., Watson, C., Baggs, E.M., Cardenas, L.M., 2017. "Hot spots" of N and C impact nitric oxide, nitrous oxide and nitrogen gas emissions from a UK grassland soil. Geoderma 305, 336–345. https://doi.org/10.1016/j.geoderma.2017.06.007.
- Louca, S., Polz, M.F., Mazel, F., Albright, M.B.N., Huber, J.A., O'connor, M.I., Ackermann, M., Hahn, A.S., Srivastava, D.S., Crowe, S.A., Doebeli, M., Parfrey, L.W., 2018. Disentangling Function From Taxonomy in Microbial Systems Function and Functional Redundancy in Microbial Systems. https://doi.org/10.1038/s41559-018-0519-1.
- Makiola, A., Dickie, I.A., Holdaway, R.J., Wood, J.R., Orwin, K.H., Glare, T.R., 2019. Land use is a determinant of plant pathogen alpha- but not beta-diversity. Mol. Ecol., mec.15177 https://doi.org/10.1111/mec.15177.

Martin, M., 2011. Cutadapt removes adapter sequences from high-throughput sequencing reads. EMBnet.journal 17, 10. https://doi.org/10.14806/ej.17.1.200.

- Mikha, M.M., Rice, C.W., Milliken, G.A., 2005. Carbon and nitrogen mineralization as affected by drying and wetting cycles. Soil Biol. Biochem. 37, 339–347. https://doi. org/10.1016/j.soilbio.2004.08.003.
- Mooshammer, M., Wanek, W., Hämmerle, I., Fuchslueger, L., Hofhansl, F., Knoltsch, A., Schnecker, J., Takriti, M., Watzka, M., Wild, B., Keiblinger, K.M., Zechmeister-Boltenstern, S., Richter, A., 2014. Adjustment of microbial nitrogen use efficiency to carbon:nitrogen imbalances regulates soil nitrogen cycling. Nat. Commun. 5, 3694. https://doi.org/10.1038/ncomms4694.
- Philippot, L., Hallin, S., Schloter, M., 2007. Ecology of denitrifying prokaryotes in agricultural soil. Adv. Agron. 2113, 249–304. https://doi.org/10.1016/S0065-2113 (07)96003-4.
- Porre, R.J., van Groenigen, J.W., De Deyn, G.B., de Goede, R.G.M., Lubbers, I.M., 2016. Exploring the relationship between soil mesofauna, soil structure and N2O emissions. Soil Biol. Biochem. 96, 55–64. https://doi.org/10.1016/j. soilbio.2016.01.018.
- Puri, G., Ashman, M.R., 1998. Relationship between soil microbial biomass and gross N mineralisation. Soil Biol. Biochem. 30, 251–256. https://doi.org/10.1016/S0038-0717(97)00117-X.
- R Development Team, 2018. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
- Rawls, W.J., Pachepsky, Y.A., Ritchie, J.C., Sobecki, T.M., Bloodworth, H., 2003. Effect of soil organic carbon on soil water retention. Geoderma 116, 61–76. https://doi. org/10.1016/S0016-7061(03)00094-6.
- Rognes, T., Flouri, T., Nichols, B., Quince, C., Mahé, F., 2016. VSEARCH: a versatile open source tool for metagenomics. PeerJ 4, e2584. https://doi.org/10.7717/peerj.2584.
- Rumpel, C., Kögel-Knabner, I., 2011. Deep soil organic matter—a key but poorly understood component of terrestrial C cycle. Plant Soil 338, 143–158. https://doi. org/10.1007/s11104-010-0391-5.
- Saggar, S., Jha, N., Deslippe, J., Bolan, N.S., Luo, J., Giltrap, D.L., Kim, D.G., Zaman, M., Tillman, R.W., 2013. Denitrification and N2O: N2 production in temperate

grasslands: processes, measurements, modelling and mitigating negative impacts. Sci. Total Environ. 465, 173–195. https://doi.org/10.1016/j.scitotenv.2012.11.050.

- Schnell, I.B., Bohmann, K., Gilbert, M.T.P., 2015. Tag jumps illuminated reducing sequence-to-sample misidentifications in metabarcoding studies. Mol. Ecol. Resour. 15, 1289–1303. https://doi.org/10.1111/1755-0998.12402.
- Shipley, B., 2009. Confirmatory path analysis in a generalized multilevel context. Ecology 90, 363–368. https://doi.org/10.1890/08-1034.1.
- Sim, R.E., Moot, D.J., Brown, H.E., Teixeira, E.I., 2015. Sowing date affected shoot and root biomass accumulation of lucerne during establishment and subsequent regrowth season. Eur. J. Agron. 68, 69–77. https://doi.org/10.1016/j. eja.2015.04.005.
- Sparling, G.P., Feltham, C.W., Reynolds, J., West, A.W., Singleton, P., 1990. Estimation of soil microbial C by a fumigation-extraction method: use on soils of high organic matter content, and a reassessment of the kec-factor. Soil Biol. Biochem. 22, 301–307. https://doi.org/10.1016/0038-0717(90)90104-8.
- Spohn, M., Klaus, K., Wanek, W., Richter, A., 2016. Microbial carbon use efficiency and biomass turnover times depending on soil depth - implications for carbon cycling. Soil Biol. Biochem. 96, 74–81. https://doi.org/10.1016/j.soilbio.2016.01.016.
- St. Luce, M., Whalen, J.K., Ziadi, N., Zebarth, B.J., 2011. Nitrogen dynamics and indices to predict soil nitrogen supply in humid temperate soils. Adv. Agron. 112, 55–102. https://doi.org/10.1016/B978-0-12-385538-1.00002-0.
- Stone, M.M., DeForest, J.L., Plante, A.F., 2014. Changes in extracellular enzyme activity and microbial community structure with soil depth at the Luquillo critical zone observatory. Soil Biol. Biochem. 75, 237–247. https://doi.org/10.1016/j. soilbio.2014.04.017.
- Swensen, B., Bakken, L.R., 1998. Nitrification potential and urease activity in a mineral subsoil. Soil Biol. Biochem. 30, 1333–1341. https://doi.org/10.1016/S0038-0717 (98)00015-7.
- Tardy, V., Spor, A., Mathieu, O., Lévèque, J., Terrat, S., Plassart, P., Regnier, T., Bardgett, R.D., van der Putten, W.H., Roggero, P.P., Seddaiu, G., Bagella, S., Lemanceau, P., Ranjard, L., Maron, P.-A., 2015. Shifts in microbial diversity through land use intensity as drivers of carbon mineralization in soil. Soil Biol. Biochem. 90, 204–213. https://doi.org/10.1016/J.SOILBIO.2015.08.010.

- Tian, Q., Wang, X., Wang, D., Wang, M., Liao, C., Yang, X., Liu, F., 2017. Decoupled linkage between soil carbon and nitrogen mineralization among soil depths in a subtropical mixed forest. Soil Biol. Biochem. 109, 135–144. https://doi.org/ 10.1016/j.soilbio.2017.02.009.
- Tiedje, J.M., 1994. Denitrifiers. In: Methods of Soil Analysis. John Wiley & Sons, Ltd, pp. 245–267. https://doi.org/10.2136/sssabookser5.2.c14.
- Trolove, S., Thomas, S., van der Klei, G., Beare, M., Cichota, R., Meenken, E., 2019. Nitrate leaching losses during pasture renewal – effects of treading, urine, forages and tillage. Sci. Total Environ. 651, 1819–1829. https://doi.org/10.1016/j. scitotenv.2018.09.333.
- Uksa, M., Schloter, M., Kautz, T., Athmann, M., Köpke, U., Fischer, D., 2015. Spatial variability of hydrolytic and oxidative potential enzyme activities in different subsoil compartments. Biol. Fertil. Soils 51, 517–521. https://doi.org/10.1007/s00374-015-0992-5.
- Wang, H., Li, Xu., Li, Xiang, Li, Xinyu, Wang, J., Zhang, H., 2017. Changes of microbial population and N-cycling function genes with depth in three Chinese paddy soils. PLoS One 12, 1–16. https://doi.org/10.1371/journal.pone.0189506.
- Wang, Q., Garrity, G.M., Tiedje, J.M., Cole, J.R., 2007. Naïve bayesian classifier for rapid assignment of rRNA sequences into the new bacterial taxonomy. Appl. Environ. Microbiol. 73, 5261–5267. https://doi.org/10.1128/AEM.00062-07.
- Yeomans, J.C., Bremner, J.M., McCarty, G.W., 1992. Denitrification capacity and denitrification potential of subsurface soils. Commun. Soil Sci. Plant Anal. 23, 919–927. https://doi.org/10.1080/00103629209368639.
- Yost, J.L., Hartemink, A.E., 2020. How deep is the soil studied an analysis of four soil science journals. Plant Soil 452, 5–18. https://doi.org/10.1007/s11104-020-04550z.
- Yuan, H., Qin, S., Dong, W., Hu, C., Manevski, K., Li, X., 2019. Denitrification rate and controlling factors for accumulated nitrate in the deep subsoil of intensive farmlands: a case study in the North China plain. Pedosphere 29, 516–526. https:// doi.org/10.1016/S1002-0160(17)60472-7.
- Zhang, B., Penton, C.R., Xue, C., Quensen, J.F., Roley, S.S., Guo, J., Garoutte, A., Zheng, T., Tiedje, J.M., 2017. Soil depth and crop determinants of bacterial communities under ten biofuel cropping systems. Soil Biol. Biochem. 112, 140–152. https://doi.org/10.1016/j.soilbio.2017.04.019.