






Research article

Modelling and mapping of subsurface nitrate-attenuation index in agricultural landscapes

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ARTICLE INFO

Handling editor: Lixiao Zhang

Keywords:

Agriculture
Water quality
Nitrate attenuation
Groundwater redox conditions
Machine learning
Extreme gradient boosting

ABSTRACT

Environmental management of nutrient losses from agricultural lands is required to reduce their potential impacts on the quality of groundwater and eutrophication of surface waters in agricultural landscapes. However, accurate accounting and management of nitrogen losses relies on a robust modelling of nitrogen leaching and its potential attenuation – specifically, the reduction of nitrate to gaseous forms of nitrogen – in subsurface flow pathways. Subsurface denitrification is a key process in potential nitrate attenuation, but the spatial and temporal dynamics of where and when it occurs remain poorly understood, especially at catchment-scale. In this paper, a novel Landscape Subsurface Nitrate-Attenuation Index (*LSNAI*) is developed to map spatially variable subsurface nitrate attenuation potential of diverse landscape units across the Manawātū-Whanganui region of New Zealand. A large data set of groundwater quality across New Zealand was collated and analysed to assess spatial and temporal variability of groundwater redox status (based on dissolved oxygen, nitrate and dissolved manganese) across different hydrogeological settings. The Extreme Gradient Boosting algorithm was used to predict landscape unit subsurface redox status by integrating the nationwide groundwater redox status data set with various landscape characteristics. Applying the hierarchical clustering analysis and unsupervised classification techniques, the *LSNAI* was then developed to identify and map five landscape subsurface nitrate attenuation classes, varying from very low to very high potential, based on the predicted groundwater redox status probabilities and identified soil drainage and rock type as key influencing landscape characteristics. Accuracy of the *LSNAI* mapping was further investigated and validated using a set of independent observations of groundwater quality and redox assessments in shallow groundwaters in the study area. This highlights the potential for further research in up-scaling mapping and modelling of landscape subsurface nitrate attenuation index to accurately account for spatial variability in subsurface nitrate attenuation potential in modelling and assessment of water quality management measures at catchment-scale in agricultural landscapes.

1. Introduction

Around the world, the need to provide food and fibre to growing populations has led to the intensification of agricultural land (Alexander et al., 2015; Fróna et al., 2019; Godfray and Garnett, 2014; Tschamtker et al., 2012). This has subsequently led to an increase in the leaching and runoff of agriculturally sourced nutrients to receiving waters, causing eutrophication and related environmental and human-health issues (Keatley et al., 2011; Savage et al., 2010; Withers et al., 2014). Inorganic nitrogen is a readily available nutrient for algae/periphyton growth in streams and rivers, posing potential toxicity effects to aquatic life, and degrading drinking water quality supplies posing risks to human health. Nitrate is generally the main form of inorganic nitrogen leached to

groundwaters and in streams and rivers (Dymond et al., 2013; Mcdowell et al., 2009). In New Zealand, the National Policy Statement for Freshwater Management has been developed to reduce nutrient losses and meet water quality objectives on a regional basis (Ministry for the Environment, 2020). As a response, various good management practices and land use scenarios need to be modelled to help assess where and how nitrate losses from agricultural lands are to be reduced or managed at catchment-scale. However, due to varying rates of potential nitrate attenuation ‘reduction’ in subsurface environments, it is difficult to accurately model these scenarios (Elwan, 2018; Singh et al., 2017a; Snelder et al., 2020). To overcome these challenges, new knowledge and tools to map and model spatially variable subsurface nitrate attenuation capacities at landscape unit scale are required for the development of

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<https://doi.org/10.1016/j.jenvman.2025.125628>

Received 1 October 2024; Received in revised form 13 March 2025; Accepted 29 April 2025

Available online 5 May 2025

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targeted and effective mitigation strategies for nitrate losses from agricultural lands.

Nitrate's transport and fate in the subsurface is strongly influenced by landscape characteristics such as soil type, underlying geology and groundwater chemistry (Elwan, 2018; Jahangir et al., 2012; McAleer et al., 2017; Orr et al., 2016; Rivas et al., 2017). In this study, these landscape characteristics are referred to as landscape factors, which can be mapped to assess their potential influence on nitrate attenuation in the subsurface environment. Denitrification, where nitrate is transformed to gaseous forms of nitrogen under favourable conditions (Korom, 1992; Rivett et al., 2008), is usually the primary pathway for nitrate attenuation in subsurface flow pathways (Clague et al., 2015a, 2019; Collins et al., 2017; Jahangir et al., 2013a; Rivas et al., 2017, 2020). However, field-based measurements of subsurface denitrification are complicated, conducted infrequently, and limited to only a few regions with a narrow range of soil and rock type combinations (Burbery, 2018). This lack of relevant data makes it difficult to correlate subsurface denitrification potential with the natural variability of landscape characteristics, posing a practical challenge for predicting and mapping landscape subsurface nitrate attenuation potential.

To gain the spatial reach that subsurface denitrification data lacks, groundwater redox conditions have been used as a proxy for nitrate attenuation potential because of observations of subsurface denitrification in reduced groundwater conditions (Clague et al., 2019; Collins et al., 2017; Rivas et al., 2017, 2020; Stenger et al., 2018). With the availability of extensive data sets including those for groundwater quality, soil, and geology, variability of groundwater redox conditions have been mapped in New Zealand and elsewhere (Close et al., 2016; Knoll et al., 2020; Koch et al., 2019, 2024; Rosecrans et al., 2017; Sarris et al., 2019; Tesoriero et al., 2015, 2024; Wilson et al., 2018, 2020). While the international research effort has been focused on identifying the depth of the subsurface redox interface (Hansen et al., 2014; Koch et al., 2019; Tesoriero et al., 2015), the focus in New Zealand has been on assessment of spatial variability of groundwater redox states and the depth at which they occur (Close et al., 2016; Wilson et al., 2018, 2020). In particular, efforts have been focused on reducing selection bias in the groundwater data (Wilson et al., 2020) and reducing uncertainty in assessment of groundwater redox status across different landscapes (Sarris et al., 2024).

However, a robust management of water quality measures require tools to estimate and reduce nitrate fluxes in different flow pathways from agricultural lands at catchment-scale. While methods have been developed and refined to estimate catchment-scale nitrogen loads (Fraser, 2021; Snelder et al., 2017, 2020), the gap that currently exists is a robust assessment and effective accounting of subsurface nitrate attenuation in New Zealand catchments (Singh et al., 2017b; Snelder et al., 2020). Accounting of subsurface nitrate attenuation can inform both farm- and catchment-scale land use decisions and implementation of targeted water quality measures. However, further research is required to develop practical tools for a robust assessment and accounting of subsurface nitrate attenuation potential at catchment-scale that can accurately represent estimation and reduction of nitrate loads to streams and rivers in agricultural landscapes.

This paper aimed to review and further develop a Landscape Subsurface Nitrate-Attenuation Index (*LSNAI*) to map subsurface nitrate attenuation potential of diverse hydrogeological settings across the Manawatū-Whanganui region, located in the lower North Island of New Zealand. It defines *LSNAI* and presents a novel methodology for analysing and integrating landscape hydrogeological variability, groundwater redox assessments, and on-farm shallow groundwater observations to predict and validate a regional-scale *LSNAI* map of different landscape units across the study area. Whereas previous studies predicting New Zealand groundwater redox conditions have employed linear discriminant analysis (Close et al., 2016; Wilson et al., 2018), or tested a range of machine learning algorithms (Friedel et al., 2020), this study evaluates and applies Extreme Gradient Boosting (XGBoost) to

predict groundwater redox status (Chen and Guestrin, 2016). XGBoost is a flexible algorithm which is increasingly being used in hydrological studies (Niazkar et al., 2024; Ransom et al., 2022). This study develops a novel modelling approach, integrating applications of machine learning (XGBoost) and unsupervised classification techniques, to classify and map spatially variable subsurface nitrate attenuation potential of different landscape units. A robust approach is taken to validating predictions by using field-scale measurements of shallow groundwater denitrification and redox data to independently verify landscape unit subsurface redox classifications. Finally, the landscape unit subsurface redox predictions and key landscape factors learned from the model training process are used to classify and map landscape units into groups of relatively high to low subsurface nitrate attenuation potential classes. The study provides new insights into the spatial variability of landscape factors' potential influences on subsurface nitrate attenuation and its transport pathways from agricultural lands to receiving waters in diverse hydrogeological landscapes. It generates new information and knowledge to further develop accurate catchment-scale water quality models to robustly quantify potential impacts of various land use scenarios and management practices for targeted and effective water quality measures across agricultural landscapes.

2. Data and methods

2.1. Study area

This study focused as a case study on the Manawatū-Whanganui region of New Zealand, also known as the Horizons region (Fig. 1). The region covers 22,215 km² (2,221,500 ha) and is characterised by several large river catchments that discharge into the Tasman Sea on the west coast (Fig. 1a). Local geology ranges from Mesozoic-age basement greywacke exposed in the southern part of the region; an abundance of unconsolidated Plio-Pleistocene-age deposits throughout; and volcanic deposits in the north (Begg et al., 2005) (Fig. 1b). The Manawatū catchment is divided by two mountain ranges, known as the Ruahine and Tararua ranges, with the river flowing east to west through a narrow gorge, known as the Manawatū Gorge (Fig. 1a and b). These two mountain ranges are formed by greywacke bedrock, shown in Fig. 1b, with Ruahine in the north and Tararua in the south.

Groundwater resources are limited to two distinct basins that have developed either side of the Ruahine and Tararua ranges (Fig. 1c). On the eastern side, unconsolidated gravel and sand within the main river valleys, which rest on Tertiary-age mudstone, forms the main groundwater resource across Tararua valleys in the Manawatū catchment (Zarour, 2008). The groundwater resources on the western side are part of the Whanganui Basin, a deep sedimentary basin characterised by marine and alluvial deposits (Carter and Naish, 1998). Groundwater recharge and discharge dynamics also differ between these basins. On the eastern side, rainfall recharge infiltrates quickly into the shallow aquifer and discharges into the local rivers making for relatively short groundwater mean residence times (Morgenstern et al., 2017). Groundwater recharge is thought to reach much deeper depths on the western side, with groundwater discharging at the coastal margin into shallower groundwater and springs due to an upwards vertical hydraulic gradient (Thomas, 2017). Groundwater mean residence times are also significantly longer on the western side (Morgenstern et al., 2017). However, in most cases, groundwater abstraction is associated with Late Quaternary deposits (Zarour, 2008).

Land use ranges from native forest/conservation land and low intensity farming in steep and hill country areas, to intensive agriculture such as dairy farming and cropping on the river plains and coastal areas (Fig. 1d). Soils in the region are primarily considered well-drained (Newsome et al., 2008), though drainage characteristics are highly dependent on a soil's landscape position (Cowie et al., 1967; Cowie and Rijkse, 1977). A unique feature of the region is the sand dune formations on the region's west coast that have developed over the late Holocene. A

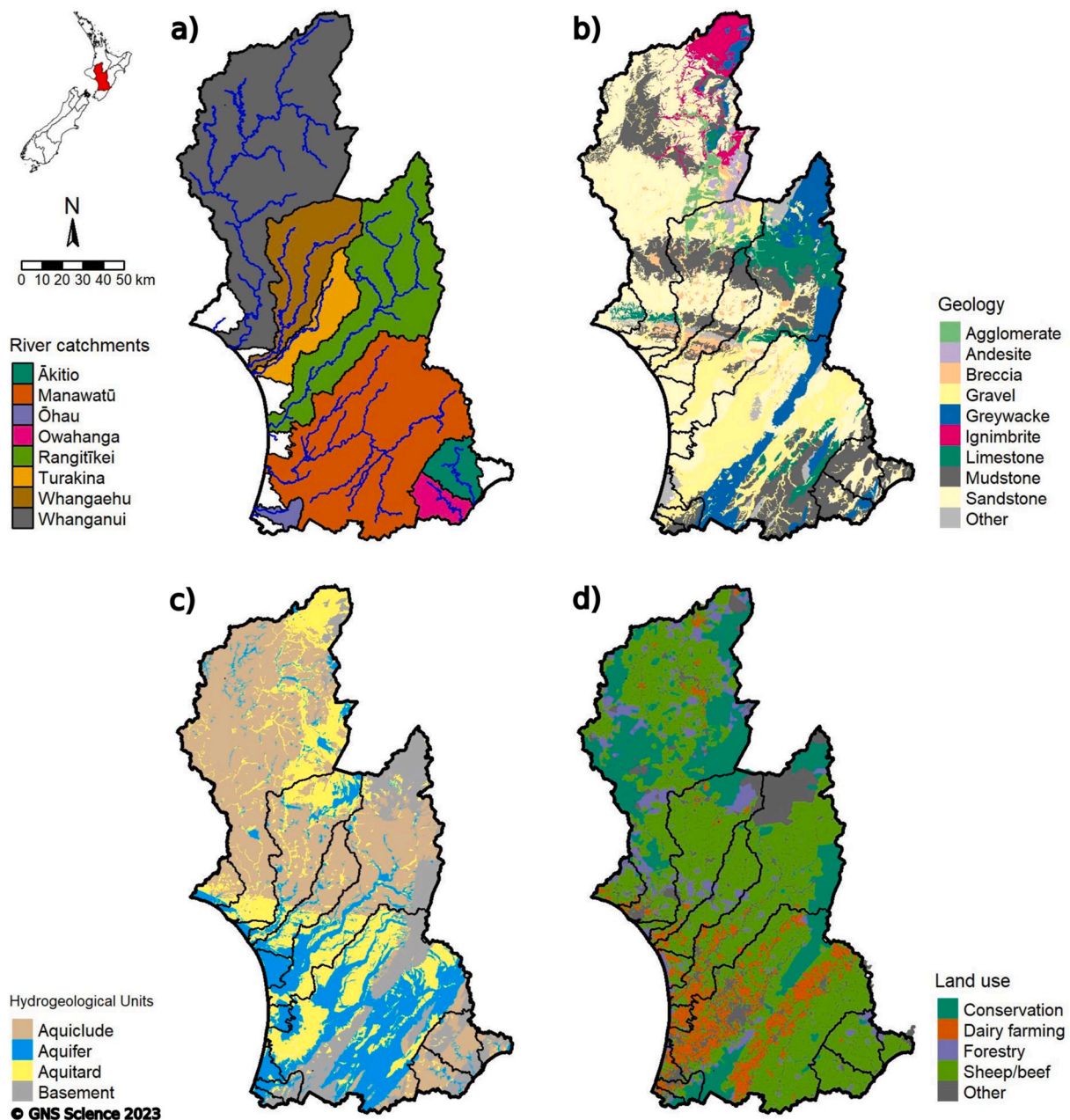


Fig. 1. Maps of a) the main river catchments, b) geological types (GNS Science, 2012), c) hydrogeological units (White et al., 2019, Revised 2023) and d) land uses (Herzig et al., 2020) across the Manawatū-Whanganui region of New Zealand, also known as the Horizons region.

major component of these dune formations is the titanomagnetite-rich ironsands that have been deposited along the coast by onshore winds, the source of which is erosion of andesitic volcanic rocks of nearby Taranaki volcanoes, located north-west of the Horizons region (Brathwaite et al., 2017).

2.2. Groundwater redox assessments and landscape characteristics

Collins et al. (2025) collated and analysed a comprehensive groundwater data set collected over the 30-year period from 1990 to 2019 across 15 regions of New Zealand. These data were collected primarily from domestic/drinking water wells, farm supply and irrigation wells, or monitoring wells. The groundwater samples were sourced from a range of depths, with most groundwater samples taken from depths of 50 m or less (Collins et al., 2025). The groundwater quality data were classified into groundwater redox status as per the groundwater redox

classification by Close et al. (2016), which was modified from McMahon and Chapelle (2008) for New Zealand conditions. It classifies groundwater redox status based on the thresholds of dissolved oxygen (DO) < 1.0 mg/L; nitrate-nitrogen (NO_3^- -N) < 0.5 mg/L; and dissolved manganese (Mn^{2+}) > 0.05 mg/L (Close et al., 2016; Collins et al., 2025). The collated groundwater dataset included some missing Mn^{2+} values (an important redox variable), which were imputed using locally-developed random forest regression models between observations of Mn^{2+} and Ca^{2+} , Mg^{2+} , K^+ , Na^+ and Cl^- values in the groundwater dataset (Collins et al., 2025). Across the study area, shallow groundwater was classified predominantly oxidised, whereas the reduced groundwater conditions were assessed more frequently at greater depths (Collins et al., 2025). Refer to Collins et al. (2025) for further details on the assessment of the collated groundwater quality dataset and its application for assessing the spatial variability and temporal stability of groundwater redox conditions across New Zealand regions. The collated national-scale

groundwater data set resulted in 34,098 individual groundwater redox assessments from 3764 wells across New Zealand, of which 1242 groundwater redox assessments were located across the Horizons region from 227 wells. [Table 1](#) summarises the basic statistics associated with the classification of the national-scale groundwater data set into either an oxidised, mixed or reduced category ([Collins et al., 2025](#)). Oxidised groundwater is the majority category and typically has higher mean and median DO and $\text{NO}_3\text{-N}$ concentrations, while reduced groundwater has higher mean and median dissolved Mn^{2+} and Fe^{2+} concentrations. This pattern conforms to the general understanding of subsurface redox conditions ([Rivett et al., 2008](#)).

Within the Horizons region, groundwater redox data was sourced from a depth of 2 m–235 m ([Table 2](#)). Like the national data set, these data were collected from groundwater wells primarily used for domestic/drinking water, farm or industrial use. The groundwater data were collected from 1990, though particularly from 2000 when the frequency and coverage of groundwater monitoring increased in the study region. Oxidised groundwater was, on average, assessed at shallower depths, compared to more mixed or reduced groundwater assessed at relatively deeper groundwater depths ([Table 2](#)).

A geographical dataset of landscape attributes and landscape unit boundaries was obtained from the New Zealand Land Resource Inventory (LRI; [Newsome et al., 2008](#)). The LRI is an inventory of five physical factors, soil, rock type, slope, presence and severity of erosion, and vegetation, mapped at a scale of 1:50,000, that drive land use capability mapping in New Zealand ([Lynn et al., 2009](#)). In addition, the LRI is supplemented with 16 additional soil properties collectively known as the Fundamental Soil Layers (FSL; [Barringer et al., 1998](#); [Newsome et al., 2008](#)). Together, these geographical data sets provide around 100,000 polygons (landscape units) across New Zealand featuring a range of landscape attributes.

In this study, a total of fourteen attributes were selected from the LRI and the FSL to represent landscape characteristics, potentially related to redox processes in the subsurface environment ([Collins et al., 2025](#)). These include top rock, base rock, slope, carbon content, gravel content, soil drainage, permeability, profile available water (PAW), pH, cation exchange capacity (CEC), phosphorus retention, potential rooting depth, flood class, and macroporosity. Each groundwater observation was spatially linked to the landscape polygon (i.e. landscape unit) in which the well was located, and the values of the corresponding landscape attributes were assigned accordingly. A complete list of these variables and their categories can be found in the supplementary data file.

In the LRI ([Newsome et al., 2008](#)), the top rock and base rock are derivations of rock type mapped across the landscape. Top rock is the first-named entire rock type, irrespective of any underlying stratigraphy and can have several lithology expressions depending on the dominance of the rock types in a single polygon unit. Base rock is the single value that identifies the principal basement lithology ([Newsome et al., 2008](#)).

Table 1

A summary of New Zealand groundwater quality data as per their redox status.

Redox Status	n	Parameter	Mean	Median	Min	Max	Standard deviation
Oxidised	23,504	DO (mg/L)	6.58	6.90	1.00	11.85	2.42
		$\text{NO}_3\text{-N}$ (mg/L)	4.90	3.80	<0.01	25.00	4.47
		Mn^{2+} (mg/L)	0.01	<0.01	<0.01	0.05	0.01
		Fe^{2+} (mg/L)	0.05	0.01	<0.01	8.20	0.18
		SO_4^{2-} (mg/L)	12.13	9.20	0.01	100.00	11.00
Mixed	4171	DO (mg/L)	2.27	1.15	0.01	11.64	2.50
		$\text{NO}_3\text{-N}$ (mg/L)	1.79	0.20	<0.01	25.00	3.49
		Mn^{2+} (mg/L)	0.26	0.10	<0.01	1.70	0.35
		Fe^{2+} (mg/L)	1.01	0.11	<0.01	15.00	2.20
		SO_4^{2-} (mg/L)	14.09	8.00	0.01	100.00	18.73
Reduced	6423	DO (mg/L)	0.21	0.15	0.01	0.99	0.20
		$\text{NO}_3\text{-N}$ (mg/L)	0.04	0.01	<0.01	0.50	0.08
		Mn^{2+} (mg/L)	0.44	0.27	0.05	1.70	0.41
		Fe^{2+} (mg/L)	2.53	1.20	<0.01	15.00	3.16
		SO_4^{2-} (mg/L)	7.53	2.60	0.01	99.90	12.96

Table 2

A summary of depth of groundwater wells, in metres below ground level, from which groundwater redox data was sourced from within the Horizons region. p25 and p75 refer to the 25th and 75th percentile.

Redox Status	n	Min (m)	p25 (m)	Median (m)	Mean (m)	p75 (m)	Max (m)
Oxidised	548	2.0	10.5	17.0	19.3	22.3	135
Mixed	134	2.0	10.6	27.0	45.9	68.6	134
Reduced	560	2.6	18.0	30.3	49.5	68.6	235

In this study, these have been merged as ‘top rock over base rock’ and reclassified as ‘Rock type’. Where top rock and base rock are the same, just the single attribute is described (e.g. ‘Greywacke over Greywacke’ becomes ‘Greywacke’) and where they are distinct, both attributes have been retained (e.g. ‘Loess over Alluvium’). In addition, for both top rock and base rock types, the various ash deposits have been reclassified as ‘volcanic ash’. Other kinds of volcanic deposits that are not ash have been reclassified as ‘volcanic deposits’. This helped reduce and simplify the number of variables for rock type.

Slope, which has eight classes, refers to a physiographic area of relatively homogeneous average relief. It is derived from stereo aerial photograph interpretation and field verification and allows up to two slope expressions within a single polygon ([Newsome et al., 2008](#)). In this study, just the first/dominant named slope attribute class has been retained (e.g. ‘Moderately steep + Steep’ becomes ‘Moderately steep’). Permeability refers to the rate at which water moves through saturated soil and includes three classes, ‘Slow’, ‘Medium’ and ‘Rapid’, of which multiple combinations are possible in layered soils ([Clayden and Webb, 1994](#)). In this study, just the first named permeability attribute class has been retained (e.g. ‘Moderate/Rapid’ becomes ‘Moderate’). The remaining attributes of carbon content; gravel; soil drainage; PAW; pH; CEC; phosphorus retention; potential rooting depth; flood class; and macroporosity have been retained as they are described in [Newsome et al. \(2008\)](#). In all cases, unrelated categories within these variables e.g., lakes, estuaries, towns/cities, have been classified as ‘Not specified’.

New Zealand’s groundwater redox data is unevenly distributed among some landscape variables ([Collins et al., 2025](#)). For example, groundwater redox data was reasonably well distributed among the different categories of carbon class, soil drainage class and permeability class. However, it was somewhat more unevenly distributed among some rock type categories. Alluvium, gravels and windblown sands were over-represented in the groundwater redox data set (relative to their New Zealand distribution), while sandstone and mudstone were under-represented. This tends to reflect the hydrogeological conditions where groundwater can be accessed, primarily those areas characterised by alluvium, gravels and windblown sands ([Zarour, 2008](#)).

2.3. Prediction of landscape unit subsurface redox status

The collated groundwater redox status and landscape factors were modelled to predict and map the subsurface nitrate attenuation potential of landscape units across the study area. The model predictions do not consider any potential for nitrate attenuation in the soil profile, unsaturated zone, riparian or in-stream environments of the landscape. However, the groundwater redox status is used as a proxy of the landscape subsurface redox status and nitrate attenuation potential, as observed by field studies in New Zealand landscapes and elsewhere (Clague et al., 2019; Collins et al., 2017; Jahangir et al., 2013b; Kruidijk et al., 2022; Rivas et al., 2017, 2020; Steiness et al., 2021; Yang et al., 2023).

The groundwater redox classification by Close et al. (2016) included a 'mixed' status, however in this study only the probability of a landscape unit being classified as either 'oxidised' or 'reduced' in its subsurface environment was predicted for classification and mapping. The mixed groundwater redox status is characterised by relatively high values across all the redox-related hydrochemistry variables (Table 1), making its implication somewhat unclear for assessment of landscape subsurface nitrate attenuation potential of a landscape unit.

The collated national-scale groundwater redox data set (Collins et al., 2025) and associated landscape attributes (Newsome et al., 2008; Supplementary Data) were used to train and test an XGBoost model that predicted a landscape unit's subsurface redox status probability as either oxidised or reduced. The XGBoost model training data set consisted of point-level groundwater redox status observations distributed across New Zealand (classified as oxidised or reduced) (Collins et al., 2025), which were used as the response variable alongside landscape-level predictors such as rock type, soil drainage and carbon classes. While only areas with groundwater redox observations available were included in the training data set, the trained model was applied to predict the subsurface redox status of all ~11,000 landscape units within the Horizons region, including those without direct groundwater redox data. This approach uses the relationships learned by the XGBoost model in the training datasets to generate robust predictions of subsurface redox status in areas lacking direct groundwater observations.

The XGBoost algorithm was used to predict landscape unit redox status probabilities for the Horizons region, i.e. $P(\text{Oxidised})$ and $P(\text{Reduced})$. The XGBoost algorithm is an ensemble tree-based machine learning method that is widely used for supervised learning tasks such as regression and classification (Niazkar et al., 2024). It is based on gradient boosting, whereby subsequent trees are trained to correct the errors of their predecessors. However, XGBoost incorporates several additional features such as regularisation and tree pruning to mitigate overfitting (Niazkar et al., 2024). XGBoost has been used in a number of groundwater and water quality studies, from predicting river nitrate concentrations (Dorado-Guerra et al., 2022; Xie et al., 2024), groundwater nitrate and manganese concentrations (Bedi et al., 2020; Collins et al., 2025; DeSimone and Ransom, 2021; Ransom et al., 2022), to assessing the occurrence of edge of field runoff (Hu et al., 2021). Although boosted regression trees have been used to predict groundwater redox conditions previously (DeSimone et al., 2020), using XGBoost for such a task is a recent development (Koch et al., 2024).

The national data set were first partitioned into training and testing data sets (75/25 split) with groundwater redox status stratified to ensure an even spread between the two data sets. A 10-fold cross-validation data set was created from the training data set for the model's hyperparameter tuning. Several data pre-processing steps were necessary prior to training. First, infrequent categories were collapsed for the Rock type variable, as there were dozens of individual attributes within this variable. Attributes that featured less than 0.5 % of the total number of landscape units were collapsed to 'other'. The remaining landscape variables (e.g. Soil drainage class, CEC class) had relatively few individual categories that did not require collapsing (See Supplementary Data). Second, as XGBoost requires the creation of dummy variables

(Kuhn and Silge, 2022), all categorical variables were converted into numerical data with one-hot encoding. Finally, predictor variables with zero variance were removed and the now-numeric data was also centred and scaled.

The model's performance was evaluated using sensitivity, specificity, accuracy, kappa (Viera and Garrett, 2005) and area under the receiver operating characteristic curve (AUC-ROC; Fawcett, 2006). Sensitivity (true positive rate) measures the proportion of cases that were correctly identified as an oxidised land unit by the model. Specificity (true negative rate) measures the proportion of cases that were correctly identified as a reduced land unit by the model. Accuracy measures the overall correctness of predictions made by the model across both oxidised and reduced land unit classes, while kappa accounts for chance agreement, offering a more robust metric for class imbalance (Viera and Garrett, 2005). The AUC-ROC evaluates the performance of a binary classification model across different threshold values. The ROC curve assesses sensitivity against 1-specificity at various threshold values. A higher value indicates better model performance.

The hyperparameters of the XGBoost model were also tuned to optimise its performance. These are settings applied to the model but are not learned during the training process (Niazkar et al., 2024). To achieve a tuned model, Latin hypercube sampling, featuring a range of 30 possible hyperparameter configurations, was used. The cross-validation folds were used to evaluate the performance of different configurations generated by the Latin hypercube. Mean AUC-ROC (across the 10 cross-validation folds) was used to select the optimal combination of hyperparameters for the model. These were then used to train the model.

All data analysis was carried out in R (R Core Team, 2022; v. 4.2.2) with predictive analysis undertaken with Tidymodels (Kuhn and Wickham, 2020; v. 1.1.1).

2.3.1. Ground-truthing landscape subsurface redox predictions

A number of local studies have been recently undertaken in the Horizons region to better understand groundwater redox conditions and the potential for denitrification in the subsurface environment (Collins et al., 2017; Collins, 2015; Gonzalez Moreno, 2019; Rivas et al., 2014, 2017, 2020; Smith et al., 2017). A range of field measurement methods were employed in these studies, including the installation of shallow groundwater piezometers; sampling and analysis of shallow groundwater quality; and single-well push-pull tests. The push-pull test is an in-situ method for a site characterisation (Istok, 2013; Istok et al., 1997) and identifying subsurface biogeochemical processes including denitrification (Addy et al., 2002; Anderson et al., 2014; Jahangir et al., 2013a; Rivas et al., 2014). The observations and results of these existing local studies in the Horizons region were collated and used to provide independent validation of the XGBoost model's predictions of landscape unit subsurface redox status across the study area.

2.4. Development of the landscape subsurface nitrate-attenuation index

The *LSNAI* was developed by classifying the Horizons region's ~11,000 landscape units into five distinct clusters using hierarchical clustering (Everitt et al., 2011). A landscape unit was defined as a spatial area, or unit of territory, that shares similar physical and geographic characteristics (Campos-Campos et al., 2018). The classification was achieved by integrating the XGBoost model's landscape subsurface redox status predictions and associated key influencing landscape characteristics of rock type and soil drainage. Rock type and soil drainage were chosen due to their significant roles observed in nitrate attenuation in the subsurface environment (Elwan, 2018; Jahangir et al., 2012; McAleer et al., 2017; Orr et al., 2016; Rivas et al., 2017) and their high variable importance scores in the XGBoost model.

A hierarchical (agglomerative) clustering analysis was applied for its interpretability and ability to provide meaningful clusters of similar landscape units. The number of *LSNAI* clusters was determined to achieve a distinct range of mean subsurface redox status probabilities (P

(*Oxidised*) and *P(Reduced)*). This classification approach resulted in hierarchical clusters ranging from Very low nitrate attenuation potential, characterised by a high *P(Oxidised)* and low *P(Reduced)* redox status, to Very high nitrate attenuation potential, characterised by a high *P(Reduced)* and low *P(Oxidised)* redox status. These classes represent the relative potential of subsurface nitrate attenuation assessed for different landscape units in the Horizons region, forming the basis of the development of the *LSNAI* for classification and mapping of landscape units and their subsurface nitrate attenuation potential in agricultural landscapes.

3. Results and discussion

3.1. Prediction of landscape unit subsurface redox status

The pre-processing steps outlined above resulted in a total of 73 features to train the XGBoost model. The 10 cross-validation folds were used to optimise the model's hyperparameters, with a range of values tested during the tuning process (Table 3). The combination of values that yielded the highest mean AUC-ROC result across the 10 cross-validation folds was selected to train the final model.

Model performance was evaluated using the held-out testing data set, which was not used during model training. The testing data set results showed a sensitivity (the true positive rate for oxidised conditions) of 0.96 and a specificity (the true negative rate for reduced conditions) of 0.80. This implies the model is more effective at identifying oxidised conditions than reduced. The relatively higher sensitivity compared to specificity is likely a result of class imbalance in the data set, where oxidised conditions were more prevalent. The overall rate of accuracy on the testing data was 0.93, with a kappa statistic of 0.78 and an AUC-ROC of 0.97. The lower kappa value, compared to the higher accuracy, is also consistent with class imbalance.

As the model was trained on the national data set, but only applied to the Horizons region, these metrics have also been calculated for training and testing data within the study area (Table 4). The model's performance for training and testing data within the study area was similar for

Table 3

Hyperparameter values used to tune the XGBoost model, and the optimised values used to train the model.

Hyperparameter name (Tidymodels alias)	Description ^a	Hypercube range	Optimal value
Learning rate (learn_rate)	The rate at which the boosting algorithm adapts from iteration to iteration.	1.35e-10 – 7.15e-02	0.07
Number of rounds (trees)	The number of trees contained in the ensemble.	7–1796	296
Maximum tree depth (tree_depth)	The maximum depth of the tree i.e. number of splits.	1–15	7
Minimum child weight (min_n)	The minimum number of data points in a node that is required for the node to be split further.	2–40	4
Gamma (loss_reduction)	The reduction in the loss function required to split further.	2.37e-10 – 18.17	5.74e-10
Subsample (sample_size)	The proportion of data that is exposed to the fitting routine.	0.13–1.00	0.74
Column sample by node (mtry)	The proportion of predictors that will be randomly sampled at each split when creating the tree models.	0.12–0.98	0.34
Early stopping (stop_iter)	The number of iterations without improvement before stopping.	3–20	18

^a Kuhn & Vaughan (n.d.) *Boosted trees*. Retrieved August 8, 2024, from https://parsnip.tidymodels.org/reference/boost_tree.html.

Table 4

The XGBoost model performance metrics calculated for the training and testing data for prediction of landscape subsurface (groundwater) redox status. The number of data points in each testing and training data set are in parentheses.

Metric	National data set		Horizons data set	
	Training (21,029)	Testing (7011)	Training (815)	Testing (285)
Sensitivity	0.97	0.96	0.96	0.98
Specificity	0.80	0.80	0.88	0.82
Accuracy	0.94	0.93	0.92	0.90
Kappa	0.79	0.78	0.84	0.81
ROC-AUC	0.97	0.97	0.96	0.96

the model trained using the national data set (Table 4), except for a slightly higher specificity and kappa, demonstrating a slight improvement on the model's ability to predict reduced conditions in the study region, compared to nationally.

The trained XGBoost model was used to predict the subsurface redox status probability for each landscape unit in the Horizons region (Fig. 2). The results demonstrate widely variable landscape subsurface redox conditions throughout the region, with some areas likely to be more strongly oxidising and other areas likely to be more strongly reducing. While no subsurface redox assessment has been completed specifically for the Horizons region, Wilson et al. (2020) produced a national-scale groundwater redox assessment for New Zealand, exempting the mountainous and steep areas of the country. Wilson et al.'s (2020) assessment predicted groundwater (subsurface) redox conditions at various depths (15 m, 50 m and 80 m) with a vertical redox gradient apparent in some areas over this range. There are broad similarities between the predictions in this study (Fig. 2) and those of Wilson et al. (2020), but specific subsurface redox depth was not examined here, due to this study's focus on predicting the probability of a landscape unit's subsurface redox status. The results of this study (Fig. 2) and those of Wilson et al. (2020), both indicate a greater likelihood of oxidising subsurface conditions in the northern part of the region and reducing subsurface conditions in the south-west coastal area. The northern part of the region features volcanic deposits in addition to various sedimentary marine deposits such as sandstone and mudstone (Fig. 1b). Significantly older basement greywacke also outcrops in the north-east of the region (Fig. 1b). In the south, the western coast is characterised by alluvial and marine sedimentary deposits including sands and gravel. Iron-rich windblown sands form a thin veneer across this area with sand dunes aligned with the predominant north-west wind direction. The axial ranges, dividing the south-east of the region with the south-west, were unmodelled by Wilson et al. (2020), but were predicted as being strongly oxidising landscapes in this analysis (Figs. 2 and 1).

Fig. 3 plots the variable importance scores calculated from the trained XGBoost model. The most important variables in assessing landscape subsurface redox conditions were scored as poorly drained soils and alluvium rock type. In this context, soil drainage characteristics are based on the depth and duration of water tables inferred from soil colours and mottles; while alluvium refers to undifferentiated floodplain alluvium, colluvium and glacial drift (Newsome et al., 2008). Soil drainage and sediment type have previously been associated with denitrification and reducing conditions in groundwater (Clague et al., 2015b, 2019; Collins et al., 2017; Rivas et al., 2017; Wu et al., 2018). Wu et al. (2018) found that a low permeability silty clay layer within a Beijing aquifer attenuated nitrate at about twice the rate of an overlying medium grain sand layer. In New Zealand, Clague et al. (2019) observed higher denitrification potential under imperfectly/poorly drained soils compared to well-drained soils in the Reporoa Basin, Waikato; while Rivas et al. (2020) noted that sites underlain by alluvium had greater subsurface denitrification potential than those with loess over gravel. Similarly, Collins et al. (2017) observed denitrification occurring in shallow groundwaters at three sites characterised by poorly-drained

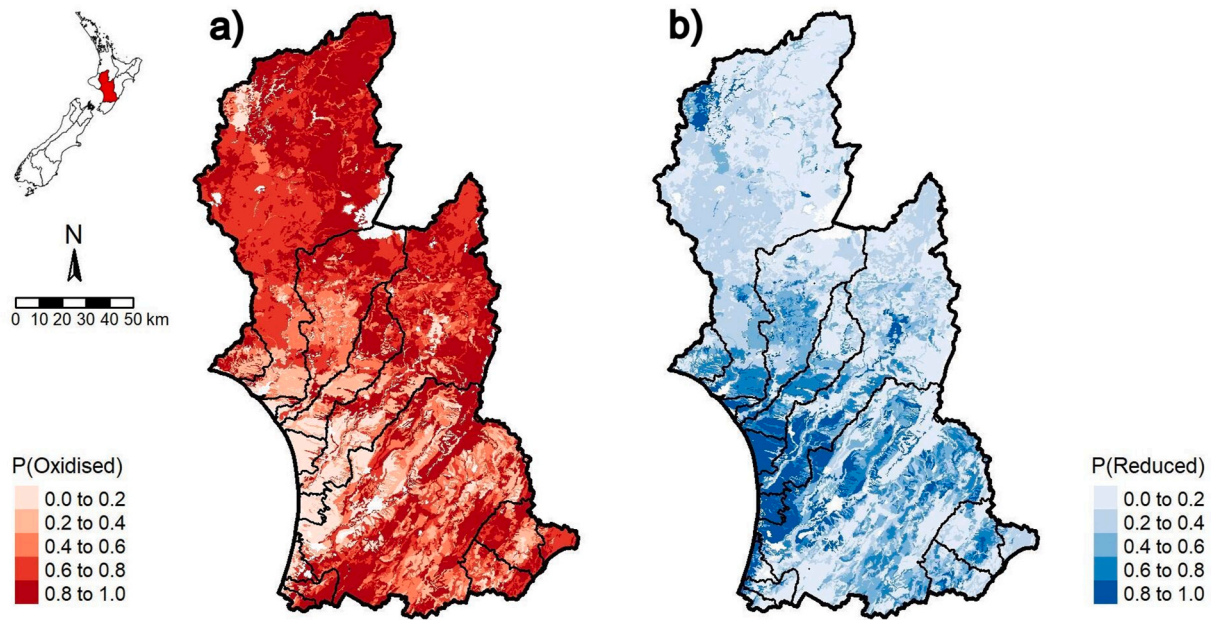


Fig. 2. Predicted landscape subsurface redox status determined by the XGBoost model: a) probability that landscape units are oxidised; b) probability that landscape units are reduced. A higher probability value indicates a greater level of confidence in the prediction.

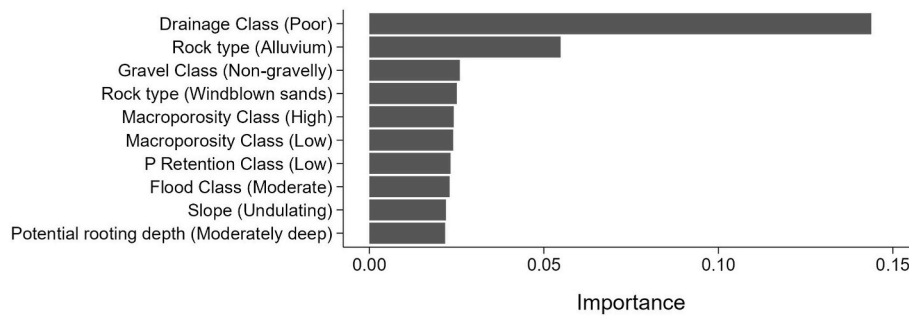


Fig. 3. Top ten variable importance scores calculated from the trained XGBoost model to predict landscape redox status in the Horizons region.

coastal soil types.

3.1.1. Ground-truthing of landscape subsurface redox predictions

Ground-truthing the results of the XGBoost model involved comparing the predicted landscape subsurface redox status, as *P(Oxidised)* or *P(Reduced)*, with observations of shallow groundwater redox status established through field techniques from previous studies within

the Horizons region (Fig. 4 and Table 5). The redox status at each of these sites has been established either through shallow groundwater monitoring (Gonzalez Moreno, 2019; Smith et al., 2017) using McMahon and Chapelle's (2008) classification (incorporating DO, NO₃-N, Mn²⁺, Fe³⁺ and SO₄²⁻), and/or through the single-well push-pull tests by observing the concentration of NO₃-N against a conservative tracer (Collins et al., 2017; Gonzalez Moreno, 2019; Rivas et al., 2020). At each

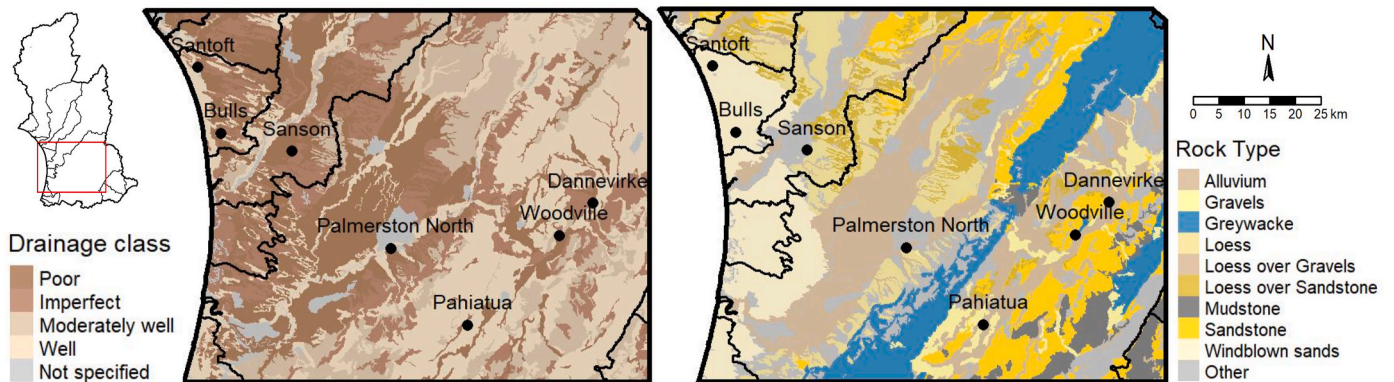


Fig. 4. Location of ground-truthing studies in the southern Horizons region showing both soil drainage class and rock type categories. Site locations do not necessarily reflect the exact locations of places they are named for.

Table 5

Shallow groundwater redox and denitrification studies, compared with the XGBoost predictions of landscape unit subsurface redox status in the Horizons region.

Reference	Piezo depth (m, below ground level)	Redox status	P (Oxidised)	P (Reduced)
Santoft sites				
Collins et al. (2017)	3.00	Reduced	0.05	0.95
Smith et al. (2017)	2.40	Reduced	0.02	0.98
Smith et al. (2017)	5.00	Reduced	0.02	0.98
Smith et al. (2017)	3.40	Reduced	0.01	0.99
Smith et al. (2017)	5.00	Reduced	0.01	0.99
Gonzalez Moreno (2019)	3.00	Reduced	0.01	0.99
Smith et al. (2017)	3.00	Reduced	0.01	0.99
Gonzalez Moreno (2019)	6.00	Reduced	0.01	0.99
Smith et al. (2017)	6.00	Reduced	0.01	0.99
Gonzalez Moreno (2019)	6.00	Mixed	0.01	0.99
Smith et al. (2017)	3.00	Reduced	0.01	0.99
Smith et al. (2017)	3.50	Reduced	0.01	0.99
Bulls sites				
Collins et al. (2017)	3.00	Reduced	0.05	0.95
Collins et al. (2017)	6.00	Reduced	0.05	0.95
Sanson sites				
Collins et al. (2017)	3.00	Reduced	0.01	0.99
Collins et al. (2017)	6.00	Reduced	0.01	0.99
Woodville sites				
Gonzalez Moreno (2019)	5.00	Reduced	0.37	0.63
Rivas et al. (2020)	5.00	Reduced	0.37	0.63
Gonzalez Moreno (2019)	6.00	Reduced	0.37	0.63
Rivas et al. (2020)	6.00	Reduced	0.37	0.63
Gonzalez Moreno (2019)	7.50	Reduced	0.37	0.63
Rivas et al. (2020)	7.50	Reduced	0.37	0.63
Pahiatua sites				
Gonzalez Moreno (2019)	3.60	Oxidised	0.70	0.30
Gonzalez Moreno (2019)	4.51	Oxidised	0.85	0.15
Gonzalez Moreno (2019)	6.40	Oxidised	0.85	0.15
Gonzalez Moreno (2019)	4.40	Oxidised	0.97	0.03
Rivas et al. (2020)	4.40	Oxidised	0.97	0.03

Table 5 (continued)

Reference	Piezo depth (m, below ground level)	Redox status	P (Oxidised)	P (Reduced)
Gonzalez Moreno (2019)	5.40	Oxidised	0.97	0.03
Rivas et al. (2020)	5.40	Oxidised	0.97	0.03
Gonzalez Moreno (2019)	6.40	Oxidised	0.97	0.03
Rivas et al. (2020)	6.40	Oxidised	0.97	0.03
Palmerston North sites				
Gonzalez Moreno (2019)	5.50	Oxidised	0.20	0.80
Rivas et al. (2020)	7.50	Reduced	0.20	0.80
Gonzalez Moreno (2019)	7.50	Reduced	0.20	0.80
Gonzalez Moreno (2019)	8.70	Reduced	0.20	0.80
Dannevirke sites				
Gonzalez Moreno (2019)	4.50	Mixed	0.70	0.30
Rivas et al. (2020)	4.50	Oxidised	0.70	0.30
Gonzalez Moreno (2019)	7.50	Reduced	0.70	0.30
Rivas et al. (2020)	7.50	Reduced	0.70	0.30

location, the individual piezometers were generally within several metres of each other, though the Pahiatua sites were up to 1 km apart. No data from these studies were used in the training of the XGBoost model.

The Santoft and Bulls sites (Table 5) were both located in the Rangitikei catchment's sand country on a sand dune complex classified geologically as windblown sand. Soils here are described in associations, where the landscape is made up of repeating phases of dune ridge, sand plain and peaty swamp (Cowie et al., 1967). Soil drainage characteristics can vary depending on the soil type and its position in the repeating phases. The studies identified in Table 5 used a combination of shallow groundwater monitoring and various push-pull tests carried out in shallow piezometers both of which suggest widespread subsurface (groundwater) reducing conditions (Collins et al., 2017; Gonzalez Moreno, 2019; Smith et al., 2017). The area is known to have strongly reducing groundwater conditions, possibly due to it being a regional discharge zone for older, more hydrochemically evolved groundwater (Morgenstern et al., 2017; Thomas, 2017), and groundwater redox conditions influenced by the high levels of iron in the sand dune deposits of volcanic origin (Brathwaite et al., 2017). The Sanson site was located further inland than the sand country, with surficial geology characterised by alluvium over gravels. The soil, Ohakea silt loam, is imperfectly-to-poorly-drained at the Sanson site. Across these three locations (Santoft, Bulls and Sanson), the local studies have determined the shallow groundwater to be largely reduced (Collins et al., 2017; Gonzalez Moreno, 2019; Smith et al., 2017). This validates the XGBoost model's prediction of a strong likelihood of reducing landscape subsurface (groundwater) conditions in this area (Table 5).

The Woodville and Pahiatua sites, which were located on the eastern side of the Manawatū catchment (Fig. 4), are more closely associated with alluvial and river deposits. The Woodville site was underlain by alluvium with soils described as silt loam and clay loam. At all three depths (5m, 6m, 7.5m below ground level) reducing groundwater conditions were measured in these field studies (Table 5), which validates

the XGBoost model's prediction of 0.63 probability suggesting high likelihood of reducing subsurface conditions at the Woodville site. At Pahiatua sites, some piezometers were installed in alluvium, while others were installed in gravels with soils described at each site as a stony silt loam. Local studies here identified oxidised groundwater conditions at the various depths tested (3.6m–6.4m below ground level). Likewise, the XGBoost model also predicted a high likelihood of Pahiatua sites being oxidised (0.70–0.97) in their subsurface environment.

The remaining two sites, at Palmerston North and Dannevirke (also in the Manawātū catchment), demonstrates the challenge of predicting landscape subsurface redox status where, potentially, a redox interface occurs at shallow depths (Table 5). In both cases, the shallowest piezometers were measured as oxidised (or mixed) groundwaters, and slightly deeper piezometers measured as reduced groundwaters (Table 5). However, the XGBoost model predicted Palmerston North as a higher probability (0.80) of reduced subsurface redox conditions (i.e. below the redox interface), while at the Dannevirke sites it predicted a greater probability (0.70) of oxidised subsurface redox (i.e. above the redox interface). While a redox interface has been observed in various subsurface environments (Böhle et al., 2002; Hansen et al., 2014; Koch et al., 2019, 2024; Kolbe et al., 2019; Refsgaard et al., 2014), it may not be a widespread occurrence throughout the Horizons region with reducing conditions found at very shallow depths in places (Table 5).

However, a high degree of correspondence between the field measurements and the predicted oxidised or reduced probabilities (Table 5) demonstrates independent validation of the trained XGBoost model's performance in modelling and mapping of subsurface redox status probabilities of different landscape units across the Horizons region.

3.2. Mapping of landscape subsurface nitrate-attenuation index

A total of five clusters were selected for the *LSNAI* based on their interpretability (Table 6), with each group exhibiting distinct mean values of $P(\text{Oxidised})$ and $P(\text{Reduced})$ across different land units. These clusters were then categorised into *LSNAI* classes ranging from 'Very low' to 'Very high', resulting in distinct distributions of soil drainage class and rock type classes (Fig. 5), as well as a spatially distributed range of *LSNAI* categories across the major catchments of the Horizons region (Fig. 6).

The 'Very low' *LSNAI* landscape class is composed of 737 land units, with a mean $P(\text{Oxidised})$ value of 0.89, i.e. highly oxidised subsurface redox conditions with very low nitrate attenuation potential, covering about 1802 km² of the study area. This class is characterised entirely by greywacke rock type (100 %), but with a range of soil drainage classes, primarily well drained (50 %) and moderately well drained (43 %) (Fig. 5).

The 'Low' *LSNAI* category, which is composed of 6033 land units, has

Table 6

Classification of Landscape Subsurface Nitrate-Attenuation Index (*LSNAI*) developed for the Horizons region. Shown are the total number of landscape units within each cluster (n); the mean probability of oxidised and reduced predictions for each cluster; the standard deviation; and the total area for each *LSNAI* class.

Landscape Subsurface Nitrate-Attenuation Index, <i>LSNAI</i> categories	Landscape units (n)	Mean P (Oxidised)	Mean P (Reduced)	Standard deviation	Area (km ²)
Very low	737	0.89	0.11	0.14	1802
Low	6033	0.78	0.22	0.20	12,422
Medium	3330	0.56	0.44	0.26	6168
High	988	0.31	0.69	0.25	1841
Very high	531	0.13	0.87	0.20	774

a mean $P(\text{Oxidised})$ value of 0.78. There is a wider range of rock types but the soil drainage class is almost entirely well drained (99 %). Rock types primarily include mudstone (13 %) and sandstone (23 %) but also includes a range of volcanic deposits (Fig. 5). This category is the largest *LSNAI* class mapped in the region (Table 6).

The 'Medium' *LSNAI* class is comprised of a balance between $P(\text{Oxidised})$ and $P(\text{Reduced})$ redox status (Table 6). Rock types in this class comprise a greater share of mudstone (25 %) and sandstone (40 %) with soil drainage class split between moderately well drained (74 %) and imperfectly drained (26 %) (Fig. 5).

The 'High' *LSNAI* class, comprising 988 landscape units, has a mean $P(\text{Oxidised})$ value of 0.31 and a mean $P(\text{Reduced})$ value of 0.69 (Table 6). These landscape units are primarily composed of poorly drained soils (79 %), with loess (31 %) and alluvium (41 %) making up the dominant rock types (Fig. 5), which covers about 1841 km² of the study area. Loess over gravels and loess over sandstone also make up minor portions of the 'High' *LSNAI* class.

Finally, the 'Very high' *LSNAI* class features a range of soil drainage classes but is exclusively composed of windblown sands (100 %) (Fig. 5), located along the western coast of the region (Figs. 6 and 1). It has a mean $P(\text{Oxidised})$ of only 0.13, or mean $P(\text{Reduced})$ of 0.87, covering 774 km² of the study area.

While a few other assessments of nitrogen attenuation have been undertaken in the Horizons region (Elwan et al., 2015; Singh and Horne, 2019; Snelder et al., 2020), only a qualitative comparison can be made between their estimation of nitrogen attenuation rates and the current study because of the different methodologies and the scales at which nitrogen attenuation has been resolved, from landscape units (Singh and Horne, 2019) to sub-catchments (Elwan et al., 2015; Snelder et al., 2020). Elwan et al. (2015) quantified the soluble inorganic nitrogen (*SIN*) attenuation factors ranging from, 0.29 to 0.75, based a mass balance approach using the differences between estimates of average annual land use nitrogen export coefficients (kg ha⁻¹ yr⁻¹) and calculated instream *SIN* yields (kg ha⁻¹ yr⁻¹) across Tararua sub-catchments in the Manawātū catchment. Snelder et al. (2020) also took a mass balance approach to calculating the total nitrogen (*TN*) attenuation coefficients (ranging from 0.1 to 0.9) for the Horizons region derived from the difference between estimates of land use based export nitrogen coefficients (kg ha⁻¹ yr⁻¹) and calculated instream *TN* yields (kg ha⁻¹ yr⁻¹) across different sub-catchments in the Horizons region. Singh and Horne (2019) developed a model for the Rangitikei catchment to account for the influence of different hydrogeological settings on *SIN* attenuation capacity across its five sub-catchments. They defined land units based on a combination of rock and soil types and calibrated nitrate attenuation coefficients to produce a landscape nitrate attenuation index (*LNAI*) of different land units across the Tararua and Rangitikei districts of the Horizons region (Singh and Horne, 2019). However, none of these methods/approaches (Elwan et al., 2015; Singh and Horne, 2019; Snelder et al., 2020) directly included information from groundwater redox conditions and landscape attributes together in their assessment of either sub-catchment scale nitrogen attenuation factor or landscape nitrogen attenuation index of different land units.

While all three models for the region (Fig. 6; Singh and Horne, 2019; Snelder et al., 2020) suggest that the magnitude of subsurface nitrate attenuation is spatially variable, there are both similarities and differences in the spatial distribution of their assessments of subsurface nitrate attenuation potential across the study area. For example, in the upper Rangitikei catchment, relatively higher potential of nitrogen attenuation have been calculated by Snelder et al. (2020) and Singh and Horne (2019), yet a relatively low *LSNAI* was assessed in this study, likely due to prediction of high $P(\text{Oxidised})$ results in this part of the catchment (Fig. 2). Wilson et al. (2020) also predicted oxidised groundwater conditions in the northern Rangitikei catchment, in contrast to both Snelder et al.'s (2020) and Singh and Horne's (2019) prediction of relatively higher nitrogen attenuation potential for upper Rangitikei catchment landscapes. However, a better agreement between the various models

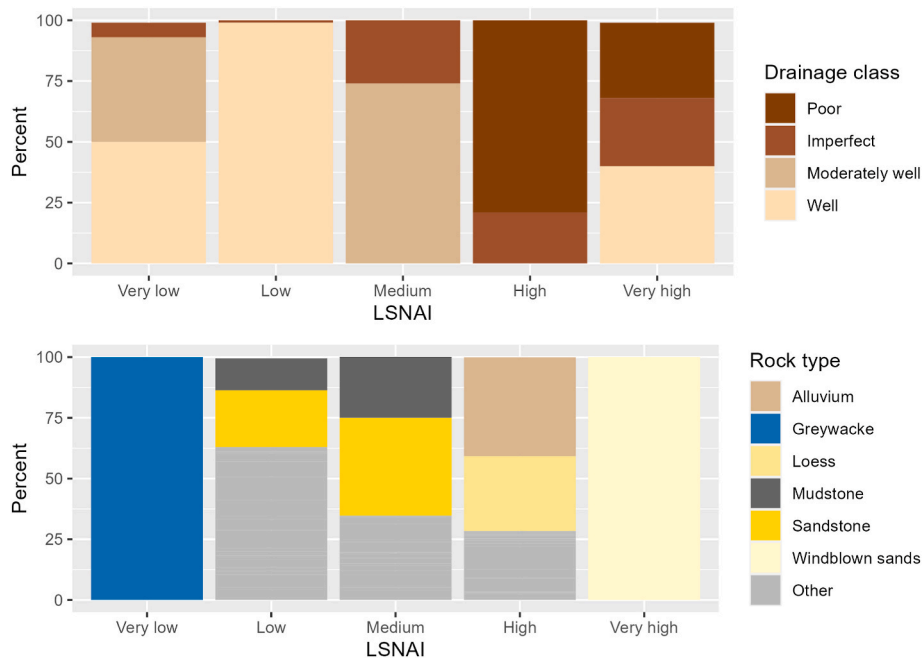


Fig. 5. Distribution of soil drainage class and rock type groupings of each Landscape Subsurface Nitrate-Attenuation Index (LSNAI) class predicted and mapped in the Horizons region.

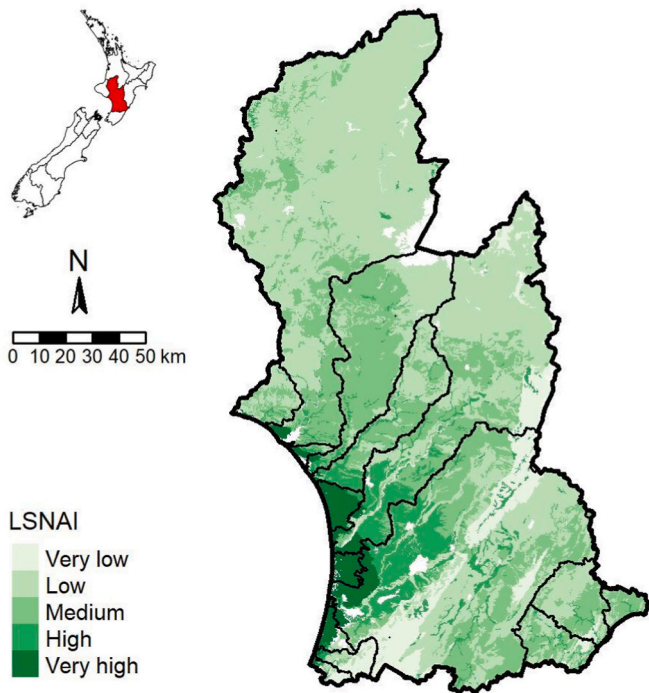


Fig. 6. Mapping of the Landscape Subsurface Nitrate-Attenuation Index (LSNAI) classes based on the hierarchical cluster analysis of groundwater redox probability predictions by the XGBoost model and soil drainage and rock type classes for the Horizons region.

(Fig. 6; Singh and Horne, 2019; Snelder et al., 2020) was observed across the eastern Manawātū catchment (also known as the Tararua catchment), where the nitrogen attenuation potential assessed in this study mostly varied between very low and medium LSNAI (Fig. 6), corresponding very well with low to medium nitrogen attenuation coefficients quantified by Snelder et al. (2020) and between low and high attenuation in Singh and Horne (2019). Also, in the Whanganui

catchment, both this study and that of Snelder et al. (2020) identified relatively low potential of nitrogen attenuation across the entire catchment.

The independent validation of XGBoost’s redox predictions provides a useful assessment of the model’s performance, however the validation studies used above, while assessing diverse soil and geological conditions, do not cover the full range of landscape types found in the Horizons region. An important source of uncertainty in this model is the somewhat narrow range of landscape characteristics that groundwater redox measurements have been drawn from. Groundwater redox data used here is particularly well represented for alluvium, loess over alluvium, volcanic deposits, windblown sands and gravel, but is underrepresented for other rock types such as greywacke, metamorphic rocks, sandstone and mudstone (Collins et al., 2025). In addition, groundwater (subsurface) redox data is widely available in locations of flat relief but lacking in steeper areas such as hill country landscapes of the Horizons region. Few studies to date report on the variability of denitrification potential in hill country subsoils and seepage wetlands in the Horizons region (Chibuikwe et al., 2019, 2024; Sanwar, 2023; Sanwar et al., 2022). However, the XGBoost model trained and tested here could pose an uncertainty in the prediction and mapping of landscape subsurface nitrate attenuation potential in steeper hill country landscapes, which makes up more than 60 % of the Horizons region. Therefore, further research is required to better characterise and understand subsurface redox conditions in these steeper landscapes, particularly hill country landscape units. This will help reduce overall uncertainty in the further development and validation of the LSNAI to comprehensively model and map spatially variable subsurface nitrate attenuation potential of different landscape units across agricultural catchments.

4. Conclusion

Meeting the water quality standards prescribed by New Zealand’s National Policy Statement for Freshwater Management requires modelling various land use scenarios and water quality measures to reduce nitrogen losses from farm-scale to catchment-scale. This study has developed a landscape subsurface nitrate-attenuation index (LSNAI) to provide an estimate of subsurface nitrate attenuation potential of

different landscape units for the Horizons region of New Zealand. The index integrates classification of groundwater redox status with key influencing landscape characteristics into the assessment and mapping of potential nitrate attenuation in the subsurface environment of different landscape units. Using a national groundwater redox data set, the machine-learning model XGBoost was trained and tested to predict landscape unit subsurface redox status for the region's ~11,000 landscape units. The model predicted a probability of oxidised or reduced subsurface (groundwater) redox conditions. XGBoost was found to be a good predictor of landscape subsurface redox status, which was also demonstrated by ground-truthing the model's predictions against independently gathered data on shallow groundwater redox conditions and nitrate attenuation measurements at various field sites located in different landscapes in the region. By combining the prediction of landscape unit subsurface redox status, with the key influencing landscape variables of soil drainage and rock type characteristics, a hierarchical clustering analysis and unsupervised classification identified and mapped five landscape subsurface nitrate attenuation potential classes. These *LSNAI* attenuation classes, mapped from Very low to Very high nitrate attenuation potential, reflect the spatially variable nature of subsurface (groundwater) redox conditions in the Horizons region, potentially allowing for subsurface nitrate attenuation accounting to be realised at catchment-scale. The developed *LSNAI* broadly identifies the lowest subsurface nitrate attenuation potential in areas where well drained soils were underlain by gravels and greywacke rock types, with increasing potential of subsurface nitrate attenuation on the plains and at the western coast with reduced groundwater conditions. However, further research and testing are required to understand the effectiveness of applying the *LSNAI* for catchment-scale modelling of nitrogen losses to waterways, especially in steeper hilly landscapes where the subsurface (groundwater) redox data is currently limited. However, an accurate mapping and accounting of *LSNAI* is expected to improve simulation of various land use scenarios across agricultural catchments, based on potential for nitrate attenuation, and provide options for targeted and effective measures on reducing nitrogen losses at catchment-scale.

CRediT authorship contribution statement

Stephen B. Collins: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Ranvir Singh:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Stuart R. Mead:** Validation, Methodology, Supervision. **David J. Horne:** Writing – review & editing, Conceptualization, Supervision.

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 study was conducted as part of a collaborative research programme between Massey University School of Agriculture and Environment (SAE) and Horizons Regional Council (HRC), New Zealand. HRC partly co-funded this study and provided in-kind support for groundwater data collected and analysed in this study. HRC co-funding and in-kind support is greatly appreciated.

Other New Zealand regional and district councils also kindly provided groundwater quality data for this study.

We also thank the anonymous reviewers whose contribution greatly improved the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jenvman.2025.125628>.

Data availability

Data will be made available on request.

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