Pasture potential estimation for dairy farms: A hybrid modelled approach using integrated industry and spatial data

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Abstract

Pasture eaten (t DM/ha) is known to be a primary driver of profitability in New Zealand pastoral dairy farm systems. However, locally relevant estimates of achievable home-grown feed eaten (the "pasture potential") are difficult to derive at industry scale. This study used a multi-stage hybrid methodology to estimate farm-specific pasture potential across a large industry dataset. Each farm was spatially enriched with environmental covariates to assign it to a farm typology system. Within each farm type, a local nitrogen response slope was estimated based on pasture eaten values for nearby farms within an expanding radius (5-120 km); local pasture eaten was then estimated as a nominal zero-N figure, to remove the confounding impact of fertiliser usage. The pasture potential value was defined as the 90th percentile of home-grown feed eaten within farms of the same type, estimated via quantile regression. A machine learning model (XGBoost) was then developed to impute values for sparsely populated typologies. The analysis identified an average distance from pasture potential of 2.5-3.5 t DM/ha across the different regions. These findings highlight the potential benefit to farms having land-specific insights into their pasture potential and support the identification of pathways for improving farm performance in terms of profitability and emissions footprint.

Keywords: Benchmarking, forage, grazing, machine learning, typology

Introduction

Pasture eaten (t DM/ha) is consistently identified as a key driver of dairy farm profitability in New Zealand pastoral systems (Neal et al. 2018), and the low cost of home-grown feed (pasture and crops) relative to imported supplements underpins the competitive advantage of New Zealand dairying internationally (Neal 2021). Across the dairying sector pasture and crop consumption typically accounts for 80-90% of total feed intake, although this varies by farm system type (Holmes et al. 2002; Clark et al. 2007) and has varied over time (Mills and Neal 2025). Carefully managing the growth and utilisation of home-grown feeds (Chapman et al. 2013; Macdonald et al. 2008) alongside the strategic use of supplementary feeds is therefore one of the central challenges and opportunities for farmers pursuing long-term profitability and business sustainability.

Despite this crucial role of home-grown feed in farm performance, there is a clear gap in the availability of typology relevant benchmarks for what a given farm's land can produce under proficient management. Coarse regional averages or provincial statistics often conflate farms situated on vastly different land, which can hinder the ability to differentiate between management issues and environmental constraints in determining the relevant pasture potential value. This challenge was acknowledged initially by the development of the DairyNZ Pasture Potential Tool, which introduced soil type and elevation into the benchmarking process (Neal et al. 2019). However, the challenges in clearly identifying this high-resolution pasture potential information may limit the value of industry pasture performance monitoring and risks misallocation of resources when they could be more targeted to drive improvements within typologies.

In the past, estimating potential pasture performance has been pursued through several approaches. First, pasture production has been estimated using empirically calibrated mathematical models such as AgPasture and McCall-Romera, where pasture growth is simulated from climate, soil, and management inputs (Romera et al. 2009; Romera et al. 2010; Andreucci et al. 2022; Li et al. 2011). These tools are most insightful at the farm scale, as they require multiple site-specific parameter inputs, which do not tend to generalise well to large population scale datasets. While benchmarking approaches such as DairyNZ benchmarking provide industry guidance, they often struggle to disentangle land-based heterogeneity which exists within a region or even within a cohort.

The aim of this study was to address these limitations by developing a methodology for estimating pasture potential across a large industry dataset. The methodology extends previous work (Neal et al. 2019), through the addition of new environmental information (slope, roughness, profile available water, drainage class, rainfall, irrigation and soil order) applied to a much larger dataset and supported by a machine

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learning model (XGBoost) to generate estimates on sparse typologies. The approach integrates industry-sourced farm data (location, home-grown feed eaten and fertiliser usage) with a number of national spatial layers, including the NZ Soil Classification (NZSC), national digital elevation model (DEM), and annual rainfall and drainage classes, to separate farms into relatively environmentally homogeneous cohorts (typologies) following the work of Monaghan et al. (2021). Within each typology, quantile regression was used to identify the 90th percentile for home-grown pasture and crop eaten. After accounting for the effect of fertiliser application, this figure is taken to be the pasture potential. Finally, a machine learning model was used to impute pasture potential for farms in sparse cohorts, yielding a continuous, farm-level potential estimate that can be used to quantify performance gaps and examine their associations with management practices at industry scale. Results are compared across typologies, regions and seasons.

Materials and Methods

Farm Data

Industry farm performance data was provided as part of a collaborative project between Fonterra, LIC and DairyNZ (DairyNZ 2025). The data consisted of annualised values across a range of farm physical and financial data, across five seasons (around 40,000 farm seasons (8,000+ farms over 5 seasons), 2020/21-2024/25). Key variables in the data included farm location (Lat/Long), milking platform area (ha), Fonterra's home-grown feed eaten (t DM/ha, estimated based on back calculation from required energy), total nitrogen fertiliser applied (kg N/ha, DairyNZ 2024a) and total irrigated area (ha).

Farm locations were converted to spatial point geometries and reprojected to the New Zealand Transverse Mercator (NZTM) coordinate reference system (LINZ 2009). Farm location was represented by a point at the dairy unit. To account for farm size, we generated a circular area around this point with the same area as the farm's milking platform. Environmental features for each farm were then estimated from the most prevalent features within this circular area. This approach is expected to carry with it a degree of inaccuracy, as no farm boundary is a perfect circle, but it does provide a simple means of estimating feature variation.

Spatial Environmental Covariates

Soil classification and properties

Soil order, profile available water (PAW), and drainage class were extracted from the Fundamental Soil Layer (FSL) dataset maintained by Landcare Research – Manaaki Whenua (Landcare Research 2000). The FSL provides polygon-based coverage of New Zealand soils classified under the New Zealand Soil Classification (NZSC; Hewitt 2010). Each farm polygon was spatially joined to the FSL layers using a largest-area overlap rule to assign the dominant soil characteristics.

Terrain

A national digital elevation model (DEM) in NZTM at 80m x 80m resolution was used to identify elevation and to compute the slope and roughness (Riley et al. 1999), using the *Terra* R Package (Hijmans 2023). The package defines *roughness* as the absolute difference between the highest and lowest points in a 3 x 3 grid of cells.

Rainfall

Mean annual cumulative rainfall (mm/year) was obtained from the HOTRUNZ baseline climate surface (1990-2020), a national gridded climate dataset which is derived from the NIWA Virtual Climate Station Network (VCSN; NIWA 2025). The rainfall spatial data was reprojected and resampled to align with the DEM grid prior to extraction.

Typology Classification

Each farm-season observation was assigned to a typological cohort or "typology" based on five stratification variables, as follows.

Elevation band

Farms were classified as low (0-50m), middle (50-200m), or (>200m) based on mean extracted elevation.

Contour band

Farms were assigned to one of five contour bands – flat (0-7 degrees), rolling (8-15), easy hill (16-25) and steep hill (26-35) and steeplands (35+). There was also an additional qualifier based on the typical roughness of the farm (in metres), that a flat contour would increase to rolling at a roughness of 5m+, rolling to easy hill at 10m+, easy hill to steep hill at 20m+ and steep hill to steeplands at 30m+. Slope angle and terrain roughness were used jointly to better discriminate terrain types, recognising that roughness can indicate undulating topography that slope angle alone may misclassify (Wilson and Gallant 2000).

Soil-drainage

Farms were classified as poorly drained (PAW within 0-90 cm greater than 100 mm, drainage class 1,2 or 3), well-drained (PAW at 90 cm above 100 mm, drainage class 4 or 5), or light (PAW at 90 cm below 100 mm) based on FSL PAW mid values and drainage class codes, providing a three-level typology capturing the dominant agronomic soil constraints relevant to pasture productivity (Hewitt 2010).

Rainfall-irrigation

A stratification approach was used (Monaghan et al. 2021) identifying farms as irrigated (>50% of farm irrigated), while for non-irrigated farms they were

grouped according to typical rainfall figures. These groups are defined as dry (<1100 mm/yr), moist (1100-1700 mm/yr), or wet (>1700 mm/yr) based on mean annual rainfall. This typology captures the dominant water supply regime, which is a key determinant of pasture productivity in New Zealand dairying systems (Chapman et al. 2009).

Season

The data was also stratified by season, to account for inter-annual variation in pasture productivity (Glassey et al. 2021).

Pasture Potential Estimations via Local Quantile Regression

Pasture potential for each farm was estimated using a local neighbourhood-based frontier approach. For each focal farm, neighbours were identified within each of five expanding radii (5 km, 10 km, 30 km, 60 km and 120 km) within the same typology combination (season, elevation band, contour band, soil drainage group, rainfall-irrigation band and NZSC soil order).

Where there were at least 10 neighbours present within a given radius, a local nitrogen response slope (capped to be between 0.005-0.022 t DM/kg N, or for every 100kg N/ha/year a response of 0.5-2.2 t DM/ha) was estimated via ordinary least squares regression (home-grown feed eaten (t DM/ha) on nitrogen fertiliser applied (kg N/ha)) across the neighbourhood. This slope was then used to estimate a nominal zero-N value for each farm, to remove the confounding role of fertiliser application (Gray 2024, DairyNZ 2024a).

The 90th percentile of the zero-N home-grown feed eaten distribution was estimated by quantile regression using an intercept-only model (Koenker and Bassett 1978; Koenker 2005), implemented using the quantreg package in R (Koenker 2023). The 90th percentile was selected as the pasture potential as it provides a parsimonious balance between outlier robustness and practical achievability, which is consistent with its use in production frontier and agricultural efficiency literature (Koenker and Hallock 2001). The farm-specific potential at the actual applied N level was recovered afterwards by re-adding the estimated contribution of N using locally determined N impact.

For farms within the minimum neighbourhood threshold (fewer than 10 farms in the typological cohort) at all radii, a valid pasture potential was unable to be estimated from the data based on observed neighbours. In this situation these farms had their pasture potential estimated via a machine learning model (XGBoost), as follows.

XGBoost Imputation for Sparse Cohorts

An XGBoost model was developed using the *xgboost* package in R to predict the zero-N potential frontier estimate from the available spatial and typological covariates (Chen and Guestrin 2016). Predictor variables included season, elevation band, contour band, NZSC soil order, soil-drainage group, rainfall-irrigation group, mean elevation, mean slope, roughness and annual cumulative rainfall. The model was trained on all available data and then used to estimate pasture potential for all farms for which estimates could not confidently be established through the standard approach described in the previous sections. Thus, the final estimates of pasture potential are formed from a hybrid approach of modelled imputation for sparse typologies and empirical statistical estimates for those with more plentiful cohorts.

Statistical Analysis

Descriptive analyses of pasture potential across regions (DairyNZ 2024b) and typologies were conducted using summary statistics such as median and interquartile range. All analyses were conducted in R (v4.5.1; R Core Team 2026) and Positron (Posit Team 2024, Wickham et al. 2019), with spatial operations executed using the sf (Pebesma 2018) and terra (Hijmans 2023) packages.

Results

Spatial Coverage and Typological Diversity

The analysis encompassed farm-season observations spanning 5 dairy seasons across most major New Zealand dairying regions (those supplying Fonterra). Among the regions, Canterbury and Waikato had the greatest typological diversity (>35 distinct typologies), with Northland the fewest (20-25). The most prevalent NZSC orders are given in ; these were Brown and Allophanic, especially throughout the Top of the South and Taranaki, respectively. Predictable trends were noted in the more regionally specific soil orders, such as Pumice, being very abundant throughout Bay of Plenty, and Ultic in Northland.

Table 2 highlights the prevalence of the other typological characteristics, indicating among a given characteristic how prevalent they are in the regions as percentages. From the table in most regions farms are low lying, except for Taranaki where far more farms were above 50m in elevation, with the greatest proportion of high elevation farms in the Bay of Plenty (BOP) and Taranaki. Dairy farms across NZ sit either in the rolling or flat contour group, though the Top of the South (TOS) has a relatively high proportion of easy hill farms at over 20% (Table 2). Drainage classes are quite mixed across the regions, Taranaki being predominantly well-drained while most other regions have a mix of poorly-drained and light drainage soils.

Unsurprisingly irrigated farms were most abundant in the Canterbury region, though with some presence in TOS (35%) and OSL (16.4%). Most other regions have

Table 1 Prevalence of soil orders (%) by region. With acronyms Bay of Plenty (BOP), Lower North Island (LNI), Top of the South (TOS), and Otago – Southland (OSL). Results are rounded to 1 decimal place.

	Prevalence (%)							
Order	**Northland**	**Waikato**	**BOP**	**Taranaki**	**LNI**	**TOS**	**Canterbury**	**OSL**
Brown	8	3	0	0	32	55	46	36
Pallic	0	0	0	0	11	1	22	35
Recent	11	2	15	5	10	34	23	13
Allophanic	5	43	10	89	7	0	0	0
Gley	20	22	10	3	35	2	8	9
Granular	9	9	0	0	0	0	0	0
Pumice	0	8	53	2	3	0	0	0
Oxidic	5	0	0	0	0	0	0	0
Podzol	2	3	4	0	0	7	0	2
Organic	6	11	8	1	2	0	1	2
Semiarid	0	0	0	0	0	0	0	2
Ultic	31	1	0	0	0	0	0	1
Melanic	3	0	0	0	1	0	0	0
Other	0	0	0	0	0	1	0	0
Raw	0	0	0	0	0	0	0	0

Table 2 Prevalence of other typology characteristics by region (% within typology group). Rounded to 1 decimal place

Typology	**Northland**	**Waikato**	**BOP**	**Taranaki**	**LNI**	**TOS**	**Canterbury**	**OSL**
High (200m+)	5	10	51	37	28	19	24	10
Middle (50-200m)	46	42	13	52	31	37	50	50
Low (0-50m)	49	48	36	12	41	44	26	40
Flat	13	37	30	33	46	20	87	56
Rolling	86	62	67	66	53	58	12	43
Easy Hill	2	1	3	1	1	21	1	1
Light	43	33	21	2	15	36	56	25
Poorly-Draining	36	12	11	11	40	14	20	32
Well-Draining	22	55	68	87	45	50	24	43
Dry	0	6	0	0	33	4	22	67
Irrigated	2	1	8	1	17	35	76	16
Moist	91	84	78	52	40	17	2	17
Wet	7	10	14	48	10	44	0	0

farms in the moist rainfall category, with LNI and OSL having the highest prevalence of dry farmland (<1100 mm/yr) at 33.4% and 66.9% respectively.

Modelling Metrics

The total dataset contained slightly over 40,000 farm seasons, with every one of these being categorised into a particular typology. Inevitably, some typologies (<20%) ended up too thinly occupied for us to establish a plausible pasture potential value; in these instances, a calibrated machine learning model (XGBoost), trained on the data for which we have pasture potential, was leveraged to estimate the missing pasture potential. The intention of the model was to use the typological

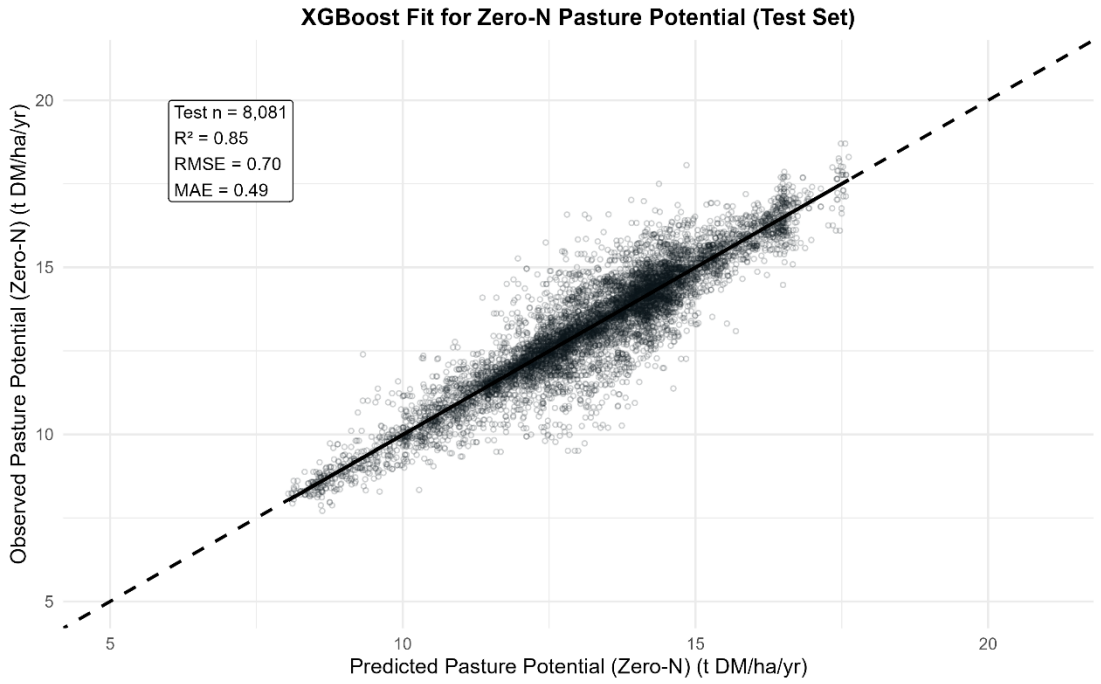


Figure 1 Comparison of the observed pasture potential vs predicted via XGBoost. The solid line is the best fit, the dashed is the 1:1, textbox displays number of observations in the test set (test n), root mean squared error (RMSE), mean absolute error (MAE) and the R^2 value

information that made up the thinly populated typology, but is also present in other well-known typologies, to establish a credible estimate. A cross-section of model performance is displayed in Figure 1. The model performed with a good R^2 value of 0.85, alongside a root mean squared error (RMSE) of 0.70 t DM/ha/y and a mean absolute error of 0.49 t DM/ha/y. These reflect strong predictions though not without a risk of inaccuracy, with a slight increase in inaccurate predictions at higher pasture potential.

Regional Pasture Potential

Having explored the prevalence of the different typological characteristics, and described the model used for sparse typologies, we turn now to exploring the variation in predicted pasture potential. Figure 2 shows the variation in pasture potential at zero applied N across the 8 regions of NZ. What is clear from Figure 2 is that Northland sits clearly towards the lower end, at around 10.5-11.0 t DM/ha while most other regions have median values in the range 12.0-15.0 t DM/ha, with Canterbury being the only region above 15.0 t DM/ha with a median of nearly 16.0 t DM/ha.

The regional variation is disaggregated further in Table 3, where the median values are shown alongside the various typological characteristics. We note that these values represent cross-sectional medians, hence are taken independently to one another. This disaggregated view highlights within region variability, for instance Northland has some typologies (flat and irrigated) which have relatively high pasture potential at 12.1 and 12.2 t DM/ha respectively, while others such as dry poorly-draining farms ranged only from 9.6 – 9.9 t DM/ha. Similar trends play out in other regions, typically low to middle elevation farms have higher pasture potential than high elevation farms. Farms on flat land have the highest pasture potential, ≥1.0 t DM/ha greater than rolling and easy hill farms. Unsurprisingly, irrigated farms often have pasture potential several tonnes greater than unirrigated systems, except for moist soil farms in the Taranaki region with an impressive 14.4 t DM/ha. These values were all estimated at a nominal zero-N. When the typical applied N levels are factored in, we see Canterbury rise most (due to a combination of relatively high applied N levels and a response rate often above 0.01 t DM/kg N in the region).

Table 4 shows the median pasture potential by soil order (note these figures cut across the other typologies such as rainfall/irrigation), with the highest values being estimated for Brown and Pallic soils (16.0-16.1 t DM/ha) on Canterbury farms, Podzols in the Waikato (14.9 t DM/ha) and Gley and Organic soils in Bay of Plenty (14.6 t DM/ha). The most prevalent soil orders in the data were Brown, Gley and Recent soils, having

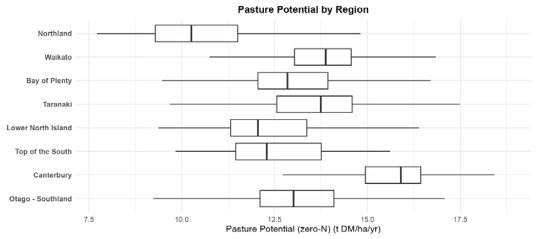


Figure 2 Regional variation of pasture potential at zero applied N

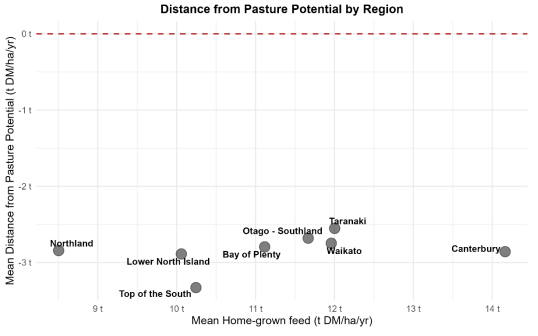


Figure 3 Average distance between the farms current home-grown feed eaten figures and the estimated pasture potential, estimated by region

representation across all studied dairying regions. Ultic soils stand out as an order that tends to perform poorly from a pasture potential perspective, ranging from 8.9-11.5 t DM/ha, Oxidic soils also appear to be a challenging soil with pasture potential of only 10.3 t DM/ha, although this is only found in Northland.

Distance from pasture potential

Figure 3 plots each region based on the average distance to pasture potential and the mean home-grown feed for the region. The figure is generated from the subset of farm data sitting below pasture potential. Expected trends are apparent in terms of the distribution of regions across the average home-grown feed figures, with Canterbury at the highest figure (>14 t DM/ha), followed by a relatively tight packing of Taranaki, Otago – Southland, Waikato and Bay of Plenty between 11 t DM/ha and 12 t DM/ha. Lower North Island and Top of the South sit near 10 t DM/ha and Northland following at around 8.5 t DM/ha. Interestingly, despite the wide range of estimates of home-grown feed eaten values and the detailed typological estimation of pasture potential, all the regions fall within a 2.5-3.5 t DM/ha range from their pasture potential. These figures also vary across the typological characteristics, with elevated (≥200 m above sea level) flat farms having some of the highest potential to improve (2.7 t DM/ha). Across soil orders we identified that Brown and Pallic had the greatest potential improvement opportunities at 2.8-3.1 t DM/ha, whilst more challenging soils such as Melanic, Ultic and Organic had finer margins of around 1.5t DM/ha on average. However, it needs to be kept in mind that that the above tables contain marginal statistics, especially when comparing across regions where features such as rainfall/irrigation may differ considerably.

Discussion

The present analysis utilised a combination of the large Fonterra dataset, a range of environmental variables and a machine learning model to make considerable advances in identifying the pasture potential at the farm level. Results were presented across different typological characteristics, highlighting where farms performed well and where they may struggle from a pasture productivity perspective. The work also highlighted a surprising uniformity regarding the distances from pasture potential, with all regions falling within a range of 2.5 – 3.5t DM/ha from the pasture potential. This work has extended previous analysis (Neal et al. 2019) through methodological advancements (the addition of machine learning to support estimation and the incorporation of several new typological aspects into the analysis), relying in part on the generation of typologies which more closely aligned to established definitions (Monaghan et al. 2021). The identification of distances from pasture potential is a key finding, which can be linked to previous analysis (Neal et al. 2017) where a simple approach was utilised to generate an economic value based on distance to pasture potential, starting from the gross yield gap and then applying assumptions about the share attributable to fixed factors, the share that could be closed by management, and the costs of doing so. The method (Neal et al. 2017) concludes that when not accounting for typological aspects outside the control of the farmer, the amount of the distance to pasture potential that can be covered profitably by managerial changes is around 12.5%. However, in the current analysis it is suggested this figure would be 25% using the same approach, as the fixed-factor component is already accounted for through typology. Taking the same approach, using an updated industry figure for the value of home-grown feed to farmer profit margins of $428/t DM (DairyNZ, 2025) we arrive at a per hectare economic value of $268 to $375 per hectare of achieving the additional 0.625 – 0.875 t DM/ha home-grown feed. Based on the range of typical farm sizes across the regions (111-243 hectares) this is a farm-scale benefit of $29,748 - $91,125 as earnings before interest and taxes.

Conclusion

This analysis highlighted the enormous variation in pasture potential across typological characteristics in the different economic farm survey regions. It

Table 3 Median Pasture Potential (Zero-N)

	Pasture Potential (Zero-N, t DM/ha)												
Region	**Low**	**Middle**	**High**	**Easy Hill**	**Flat**	**Rolling**	**Light**	**Poorly Draining**	**Well-Draining**	**Dry**	**Moist**	**Wet**	**Irrigated**
Northland	10.4	10.1	10.4	10.3	12.1	10.0	11.1	9.9	10.4	9.6	10.3	10.3	12.2
Waikato	13.9	14.1	13.3	12.1	14.3	13.7	13.9	13.6	13.9	13.5	14.0	12.5	14.4
Bay of Plenty	14.2	12.0	12.7	11.7	14.5	12.5	13.4	14.9	12.7	13.2	12.9	11.9	14.0
Taranaki	13.9	14.2	12.9	12.7	14.4	13.1	12.0	13.5	13.8	-	14.4	12.6	14.2
LNI	12.4	12.2	11.5	11.3	13.1	11.7	12.2	12.7	11.7	12.1	11.7	11.3	13.6
TOS	13.8	11.7	11.6	11.1	14.2	12.1	12.9	12.3	12.0	12.2	11.7	11.6	13.8
Canterbury	15.5	16.2	15.5	10.9	16.0	13.7	16.0	14.6	16.0	15.2	12.7	-	16.0
OSL	13.2	12.8	12.2	11.0	13.5	12.3	13.3	12.8	12.9	12.8	12.8	-	14.9

Table 4 Median pasture potential (Zero-N) by soil order

Region	**Allophanic**	**Brown**	**Gley**	**Granular**	**Melanic**	**Organic**	**Oxidic**	**Podzol**	**Raw**	**Recent**	**Ultic**	**Pumice**	**Pallic**	**Semiarid**
Northland	10.7	11.8	11.2	11.4	8.5	12.8	10.3	9.2	10.6	9.9	9.1	-	-	-
Waikato	14.0	14.0	13.8	13.5	-	14.0	-	14.2	-	11.9	8.9	13.6	-	-
Bay of Plenty	11.9	10.5	14.6	-	-	14.6	-	11.7	14.3	12.9	-	12.7	-	-
Taranaki	13.9	12.7	12.5	-	-	13.0	-	-	-	13.0	-	12.2	-	-
LNI	12.2	11.6	12.7	-	10.7	12.1	-	-	-	12.9	-	11.6	11.9	-
TOS	-	12.3	13.1	-	-	-	-	11.6	-	13.0	-	-	11.3	-
Canterbury	-	16.0	12.9	-	10.5	14.0	-	-	14.7	15.9	-	-	16.1	-
OSL	-	13.1	14.0	-	14.7	12.2	-	13.5	-	12.5	11.5	-	13.0	12.1

utilised a large industry dataset of Fonterra farm data to identify achievable pasture potential figures. This work highlights a hybrid approach utilising empirical data and a machine learning model to provide key insights into the range of pasture productivity across different farm typologies. Also identified in this work is a measure of the typical proximity to pasture potential by region, where it was identified that there is as much as 2.5-3.5 t DM/ha available per region in additional home-grown feed eaten. Using a simple methodology this was tightened to be 0.6-0.9 t DM/ha of accessible and profitable improvement to home-grown feed (Neal et al. 2017) which may translate to addition earnings before tax and interest of $29,748-$91,125 per farm based on farm size. Future work should focus on ensuring that farmers have the capacity to access this information regarding their own farm's pasture potential to ensure they can progress along a profitable pathway towards their potential home-grown feed eaten figures. This would allow farmers to gauge the home-grown feed potential of their land more accurately and configure their farm systems to capture that potential, supporting more profitable and efficient systems based on maximising home-grown feed use.

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