Using Machine Learning to Predict Dairy Production in New Zealand Based on Climate Factors

Jiqiang Wang
School of Computing
Unitec Institute of Technology
Auckland

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Contents

1 Abstract

Agriculture, and specifically dairy farming, is a foundation of New Zealand's economy, culture, and environment. The sustainability of the industry's future increasingly depends on adapting to the ever-changing relationship between dairy production and climate conditions. This study applies machine learning (ML) techniques to predict the response of cow yields to a range of climatic variables including rainfall, temperature, humidity, sunshine duration, etc. The main objective is to build a potential predictive model to support dairy farmers and industry staff to improve the decision-making process and strengthen the resilience of dairy farms in the face of climate-changing challenges. This study utilizes rich historical datasets, including several decades of climate and dairy production record data. Different ML algorithms, including time series forecasting models and regression analysis, were evaluated for their predictive accuracy and computing efficiency. The selected features significantly influenced dairy productivity, so using methods such as feature importance ranking is considered. This potential model is expected to provide valuable insights for optimizing dairy farm management practices. Through this study, we hope to provide a predictive analytical model of agriculture that could balance operational efficiency and environmental.

2 Introduction

2.1 Dairy in New Zealand

New Zealand is a leading dairy producer and contributes significantly to the global dairy market. New Zealand has a strong dairy industry, producing an estimated 21 billion litres of milk annually, which is about 3% of global milk production. This amount is the equivalent of providing 90 million people with two and a half servings of dairy products per day. With a population of just five million, New Zealand ranks as the eighth largest milk producer globally and exports an overwhelming majority of its dairy products—over 95%—to upwards of 130 countries around the world [1].

The dairy industry plays a significant role in New Zealand's economy, with apparent contributions to the national GDP. In the year ending March 2023, dairy-related activities added $11.3 billion to the economy, constituting 3.2% of the country's total GDP. Specifically, dairy farming injected $8.0 billion, which is 2.2% of GDP, while dairy processing accounted for $3.4 billion, or 0.9% of GDP, outranking other goods-producing sectors [2].

In the 2022/23 season, New Zealand's dairy industry saw record highs in herd testing and artificial insemination, with a 2.8% increase in tested cows and 3.81 million cows artificially inseminated. Dairy companies processed 20.7 billion litres of milk containing 1.87 billion kilograms of milk solids, slightly lower in volume but with a slight increase in solids compared to the previous season [3]. Despite a 3.46% decrease in the total cow population, the national average herd size rose to 441 cows, up by 39 from a decade ago [table1.1].

Table 1.1: Summary of herd statistics since 2012/13 (New Zealand Dairy Statistics 2022-23)

Season	Herds	Total cows	Total effective hectares	Average herd size	Average effective hectares	Average cows per hectare
2012/13	11,891	4,784,250	1,677,395	402	141	2.85
2013/14	11,927	4,922,806	1,716,464	413	144	2.87
2014/15	11,970	5,018,333	1,746,156	419	146	2.87
2015/16	11,918	4,997,811	1,751,704	419	147	2.85
2016/17	11,748	4,861,324	1,728,702	414	147	2.81
2017/18	11,590	4,992,914	1,755,148	431	151	2.84
2018/19	11,372	4,946,305	1,743,673	435	153	2.84
2019/20	11,179	4,921,548	1,730,374	440	155	2.84
2020/21	11,034	4,903,733	1,713,515	444	155	2.86
2021/22	10,796	4,842,122	1,701,380	449	158	2.85
2022/23	10,601	4,674,750	1,659,430	441	157	2.84

2.2 The Impact of Climate on Dairy Production

Climatic factors such as rainfall, temperature, humidity and sunshine duration significantly affect pasture growth, pasture quality and ultimately milk production and quality in on-farm dairy farming systems [4, 5]. Changes in these climate variables could lead to significant fluctuations in production, challenging the sustainability and profitability of the dairy industry [6].

Considering the volatility of climatic factors, it is important to integrate adaptive management strategies provided by accurate predictive models. This will enable dairy farmers to anticipate and respond to changing patterns of pasture growth and pasture quality to maintain consistent milk production and quality.

3 State of Research

3.1 Traditional Methods in Agricultural Predicting

Traditional agricultural forecasting methods, such as linear regression and time series analysis, have been widely used to predict milk production based on historical weather data and farm management practices [5]. However, these methods tend to ignore the nonlinear relationships and interactions between climate factors and dairy production outcomes [7].

Traditional prediction methods, while important, have limitations when dealing with complex multidimensional data. To address this problem, this research applies a new approach that combines these traditional models with machine learning techniques to provide a more detailed understanding of the basic patterns in the data.

3.2 Advancements in Machine Learning for Agriculture

Recent advances in machine learning (ML), particularly in the areas of predictive modelling and data analytics, offer new ways to improve the accuracy and reliability of agricultural forecasts [8]. Machine learning algorithms such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs) and Random Forests can capture complex patterns and non-linear relationships in large datasets to improve the prediction of dairy production under different climatic conditions [9].

This study recognises the boom in machine learning in agriculture. By exploring a range of complex machine learning models, we bridge the gap between the dynamics of climate variables and actual metrics of dairy production.

4 Models and Methods

4.1 Data Collection and Preprocessing

The study will collect historical data on climatic variables (e.g., rainfall, temperature, humidity, sunshine hours, etc.) and dairy production indicators (e.g., milk yield, fat content, protein content) from reliable sources such as meteorological agencies, dairy cooperatives, and research institutions [9, 10]. The data will undergo pre-processing steps including data cleaning, normalisation and feature engineering to ensure its accuracy and suitability for model training [11].

Data integrity is critical to the success of our ML model. Therefore, our preprocessing will also include a step to interpolate missing data to ensure full coverage of climate and production variables in all datasets.

4.2 Model Selection

Multiple ML algorithms will be thoroughly evaluated to determine the most appropriate model for predicting dairy production outcomes. Candidate models may include Support Vector Regression (SVR), Gradient Boosting Machine (GBM) and Random Forrest [12]. Model selection criteria will emphasise predictive accuracy, computational efficiency and interpretability to define a solid predictive framework for practical applications in the dairy industry [13].

To ensure careful selection, our study will be comparatively analysed through a matrix of performance indicators. This will not only affect the accuracy of each algorithm but will also improve computational efficiency and ease of interpretation.

4.3 Validation and Testing

The performance of the selected ML models will be critically evaluated using a combination of training-validation-testing datasets and cross-validation techniques [14]. The dataset will be randomly divided into a training subset (70%), a validation subset (15%) and a testing subset (15%) to assess the generalisability and robustness of the model across different climate zones and production systems [15]. In addition, k-fold cross-validation will be used to estimate the predictive uncertainty of the model and identify potential sources of bias or overfitting [16].

5 Research Value

The development of accurate and reliable machine learning-based dairy production forecasting models is important for dairy farm sustainability and profitability [17]. By combining real-time weather data and farm management information, farmers can proactively manage climate-related risks, optimise resource allocation and improve overall productivity and profitability [18]. The ability of prediction models to integrate real-time climate data highlights their use in assisting farmers to employ precision farming techniques, thereby optimising their response to climate-related risks.

This research contributes to the larger field of agricultural science by demonstrating the efficacy of machine learning techniques in predicting the response of complex biological systems to environmental change [19]. The methodological framework developed in this study can be applied to other agricultural sectors and extended to evidence-based decision-making and sustainable resource management [20]. By mapping the interactions between environmental factors and agricultural output, our study provides a blueprint for data-driven policy-making. This could guide the development of sustainable practices and provide incentives to encourage the use of predictive analyses in agriculture.

6 Conclusion

In summary, this study outlines the potential of machine learning to improve the New Zealand dairy industry's response to the unstable forces of climate change. By analysing historical data and applying advanced machine learning algorithms, this study presents a predictive model that demonstrates the harmony of agricultural knowledge and cutting-edge technology. The model is not only expected to enhance the decision-making process of dairy farmers but also to function as part of a smart agricultural system.

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