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Effect of introducing weather parameters on the accuracy of milk production forecast models

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ABSTRACT

The objective of this study was to analyze the effect of adding meteorological data to the training process of two milk production forecast models. The two models chosen were the nonlinear auto-regressive model with exogenous input (NARX) and the multiple linear regression (MLR) model. The accuracy of these models were assessed using seven different combinations of precipitation, sunshine hours and soil temperature as additional model training inputs. Lactation data (daily milk yield and days in milk) from 39 pasture-based Holstein-Friesian Irish dairy cows were selected to compare to the model outputs from a central database. The models were trained using historical milk production data from three lactation cycles and were employed to predict the total daily milk yield of a fourth lactation cycle for each individual cow over short (10-day), medium (30-day) and long-term (305-day) forecast horizons. The NARX model was found to provide a greater prediction accuracy when compared to the MLR model when predicting annual individual cow milk yield (kg), with R^2 values greater than 0.7 for 95.5% and 14.7% of total predictions, respectively. The results showed that the introduction of sunshine hours, precipitation and soil temperature data improved the prediction accuracy of individual cow milk prediction for the NARX model in the short, medium and long-term forecast horizons. Sunshine hours was shown to have the largest impact on milk production with an improvement of forecast accuracy observed in 60% and 70% of all predictions (for all 39 test cows from both groups). However, the overall improvement in accuracy was small with a maximum forecast error reduction of 4.3%. Thus, the utilization of meteorological parameters in milk production forecasting did not have a substantial impact on forecast accuracy.

1. Introduction

Over the past four decades, the influence of weather factors on dairy milk production has been explored in several studies. In areas such as Ireland, Great Britain and New Zealand, the temperate maritime climate allows for pasture-based dairy systems for the majority of the lactation period. On Irish dairy

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Abbreviations: DMY, daily milk yield; DIM, days in milk; NCM, number of cows milked; POD, percentage of difference; MLR, multiple linear regression; NARX, nonlinear auto-regressive model with exogenous input
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farms, cows are housed indoors in winter and grazed from early spring to late autumn. This allows for grazed grass to be the primary feed source for Irish dairy cows, where effective grass utilization plays an essential role in the cost efficiency of the Irish dairy industry [1,2]. Hence, the relationship between meteorological data and milk yield is of particular interest for pasture-based dairy systems, as is its impact on the prediction accuracy of milk production.

In an England and Wales based study, a linear regression model was employed to predict annual milk yield on a national level for 13 years using factors based on average milk yield of about one million cows [3]. Smith's predictions comprised of a three-stage piecemeal forecast of annual average daily milk yield (DMY) for 13 individual years (1954–1966) based on annual average daily cow production records. (1) At the end of March, a twelve months ahead forecast (multiple linear regression (MLR) model) was produced using milk production data and the additional mean March soil temperature with a mean percentage error of 0.53. At this stage, mean March soil temperature data were incorporated into the model as an indicator of grass growth for the coming season. (2) At the end of April, an eleven months ahead forecast was produced using only milk production data with a mean percentage error of 0.56. (3) At the end of June, a nine months ahead forecast was produced using milk production and rainfall data over the month of June with a mean percentage error of 0.31. At this stage, June rainfall data were incorporated in the model due to rainfall levels during the haymaking season affecting the quality of hay consumed by dairy cows for the remainder of the year. The impact of adding these weather parameters were not compared with forecasts solely based on milk production data due to the variation in forecast horizons and non-dynamic weather parameter inputs; hence the effect of applying weather parameters was not quantified. Consequently, it is not clear that the level of improvement was achieved by adding these weather parameters to the milk production forecast model. Smith's study is the sole body of work that has focused on introducing weather parameters to improve the accuracy of milk production forecasts. However, the study was limited to averaged annual figures on a countrywide milk production level, as well as only employing the MLR model without comparing additional models, which is commonly adopted in current studies. In addition, during the period of the selected study, grazing systems were far more susceptible to the effects of weather conditions as many of the grasslands management techniques and technologies employed today were not yet developed. More specifically, the web-based grassland management tool 'PastureBase Ireland (PBI)' had not yet been developed. PBI helps farmers to easily evaluate paddocks and cultivars on farms to increase dry matter yield [4]. Furthermore, some on-farm grassland management practices which can increase the efficiency of grass utilization were not yet employed such as frequency and methods of sward renewal [5].

Grass growth is affected by localized meteorological conditions which in turn, affects the milk production levels of cows primarily consuming pasture (such as in New Zealand and Ireland). Correlations between milk yield (kg/cow/day) and 16 weather factors (air temperature, soil temperature, sunshine hours, wind force, relative humidity, rainfall and evaporation rate etc.) have been analyzed and shown to produce statistically significant positive associations [6]. In particular, sunshine hours and soil temperature were found to have small positive correlations with milk yield (R-values of 0.14 and 0.25, respectively). Other weather parameters such as air temperature, relative humidity, and wind speed were found to be far less significant. Roche et al. [6] concluded that weather variables had only a small effect on milk production as pasture quality was not allowed to vary greatly on well-managed farms. Since a modern farm management system was designed to eliminate subjectivity, management can overcome the effect of weather on cow's dry matter intake [7].

In Scotland, upper levels of temperature and humidity were found to affect both milk yield and composition variability depending upon whether cows were kept in sheds or out on pasture. Furthermore, soil temperature was found to have a greater correlation with milk yield than air temperature, while sunshine hours was found to have the highest correlation with milk yield among forecast models that excluded air temperature variables. Rainfall was found to have the second lowest correlation with milk yield [8]. This research took into consideration animal welfare based on heat stress levels.

Previous Irish based studies have reported relationships between grass growth and weather parameters including: air temperature, soil temperature, solar radiation, sunshine hours and rainfall. Although the effects of weather parameters varied at different periods during the year, soil temperature was found to have a major impact on the grass growth all year around, while no strong relationship was found between rainfall and grass growth in any season of the year [9,10]. Due to highly seasonal grass growth in Ireland, Irish pasture-based cows are housed full-time from December to February and fed grass silage during the winter period. In the subsequent calving season, all cows are fed both grass silage and specified levels of concentrate feeds [11]. During the rest of the year (up until the subsequent November), cows are turned out to pasture where they feed primarily on grazed grass with additional concentrate feed offered where necessary. Herd level milk yield has been modelled while taking into account grazing management and cow's body conditions [12,13]. Ruelle et al. [13] developed a pasture-based herd level milk yield forecast model which consisted of a herd model incorporating cows' body condition, a grass model and grazing management rules. The grassland management and therefore pre-grazing grass height was an input of the herd model, an output of the grass model and a significant factor of the grazing management, respectively. Although weather parameters have been shown to effect both grass growth and herbage quality, controlled levels of supplementation feed are sometimes provided to pasture-based cows during periods of poor grass growth. In doing so, the effect of weather parameters on milk production levels is reduced. The feed allocation also took into account supplementary feed flexibility to simulate different scenarios.

Previous studies have shown that grass growth is dependent on weather parameters such as temperature, radiation and rainfall in pasture-based systems [14,15]. Soil temperature has been found to be correlated with milk yield due to both physiological (heat stress) and environmental (grazing conditions) factors [3,6,8]. Sunshine hours and rainfall were also found to influence milk production levels in cognate studies [3,6,8]. The Irish metrological service (Met Éireann) provides medium range (7–10 days) agricultural related weather forecasts, including rainfall, soil temperature and sunshine hours as well as access to historical records of weather data throughout Ireland [16].

Accurate milk production forecasts will be useful for providing farm management decision support for improving herd management, energy utilization and economic prediction. Improved management practices is of particular importance in the current volatile milk pricing environment across European member states post milking quotas. Therefore, accurate milk production forecasts have become increasingly important and could provide farmers with information related to: farm thermal cooling loads, plant capacity sizing, optimizing plant configurations and cash flow planning [17–20]. Additionally, highly accurate milk production figures could be used to help determine important factors on dairy farms such as cooling loads, water utilization, economic performance and energy consumption [20–24]. Due to practical constraints, it is difficult to adopt a holistic approach for milk yield forecasting where detailed inputs such as grass growth, feed intake, body condition and the level of the emitted pollutants are utilized [25]. Detailed farm management and cow body condition records are rarely accessible on commercial dairy farms. However, milking records such as milk yield, milking date and number of cows milked are readily available. Accurately predicting grass growth and cow level supplementary feed intake is very challenging and thus, this information is currently unavailable on commercial dairy farms [26].

Despite discussion related to the relationship between grass growth and weather parameters in Ireland, and the relationship between weather factors on dairy milk production in other countries, no previous studies have investigated the impact of introducing meteorological parameters for milk production prediction modelling for Irish pasture-based dairy farms. Hence, the contribution of this study was to test the proposed hypothesis that incorporating weather parameters into existing milk production models may improve model prediction accuracy without the need of employing detailed grass growth models or holistic dairy production models that require more detailed information.

The primary objective of this study was therefore to investigate the effect of introducing the weather parameters: soil temperature, precipitation and radiation on milk production forecasting accuracy. This was achieved by testing eight input data combinations designed to factor weather information into the model configuration and training process. As discussed above, the MLR model was included in this study as it has been proved successfully to predict annual milk yield in the study of Smith [3]. Furthermore, the MLR model can incorporate additional input variables, whereas curve fitting models (such as Wood's model) can only use days in milk (DIM) and DMY [27–29] and thus, is not suitable for assessing the impact of additional meteorological data. Additionally, the nonlinear auto-regressive model with exogenous input (NARX) model was included in this study as it offers a more sophisticated approach, which has found to be effective for short term time series analysis and non-linear system prediction [30–33].

2. Materials and methods

2.1. Data collection

The selected models were trained using two categories of data: (1) on-farm data consisting of DMY and DIM records, both of which are accessible for Irish commercial dairy farms. Empirical data comprising 928,395 daily milking records of pasture-based cows collected from experimental dairy farms (all within close proximity) situated in the south of Ireland over a five year period (2004–2008). Each daily milking record contained date of milking, time of milking, milk yield (kg) and a cow identification number. (2) Meteorological data (see Table 1) were measured from the nearest Met Éireann weather station (37 km south, Cork Airport). For the period 2004–2008, meteorological data consisted of daily rainfall (mm), sunshine hours (hour) and soil temperature (°C) data. The climate of Ireland can be described as a maritime influenced, mild and temperate climate. Hence, Ireland does not suffer from the extremes of temperature, in comparison to many other countries at similar latitude [16].

In this study, actual historical records were employed as opposed to weather forecasts due to limitations related to the accuracy of the forecasts. Forecasted data would have introduced noise and uncertainty into the simulations, which may have resulted in erroneous results related to the effect of introducing weather data on prediction accuracy. Therefore, in the present study only actual weather data were used to test the hypothesis first to see if there was any improvement in milk production forecasting accuracy.

In this study, the model simulations and evaluations were set at the individual cow level and sample cows were selected using the MPFOS (Milk Production Forecast Optimization System) [32]. The MPFOS was designed to calculate optimal model parameters, conduct statistical analysis and produce milk production forecasts for each chosen model using input data combinations based on individual milk production records and meteorological data stored in the database. Three selection rules were applied to select suitable individual test cows from the raw data over a span of five years gathered from the experimental farms. All cows that satisfied the following criteria were selected for analysis: (1) the first lactation occurred in the first model training input year, (2) a minimum of four continuous year-on-year lactation data were available (incomplete lactations were allowed, i.e. less than 305 days), and (3) milking records of the fourth lactation were complete. Integrity of milking records in the fourth lactation was vital as these records were used for validation and model performance comparisons. A previous study employing the MPFOS observed no significant improvement in model accuracy when removing the first lactation in comparison to other treatments due to underling irregularities in the parity trends [34]. Therefore, all three years of lactation records were included in the training set. The selection rules were applied to the raw data, which consisted of 779 cows over a span of five years (2004–2008). Of these, 307 cows calved in 2004 and 64 of these 307 cows were in the first lactation. Of these 64 first lactation cows, 18 cows had full datasets for four or more successive lactations and these 18 cows were selected as test group 2004. For

Table 1 – Summary of weather data collection (2004–2008, 1827 daily records) from Met Éireann weather station (37 km south of Moorepark Teagasc Food Research Centre, Co. Cork).

Weather parameter	Mean	Minimum Maximum	Median	Mode	Standard Deviation
Met Éireann weather station near Moorepark					
Rainfall	3.2	0 66.3	0.5	0	6.23
Sunshine hours	4.1	0 16.0	3.2	0	3.96
Soil temperature	10.9	1.6 22.3	10.6	8.3	4.69
Nationwide					
Rainfall	2.9	0 67.9	0.4	0	6.41
Sunshine hours	3.91	0 16.9	3.5	0	4.51
Soil temperature	10.1	0 23.5	10.1	7.1	5.12

Note: Rainfall amount (mm) over 24 h, Sunshine (hours) over 24 h, Soil temperature (°C) at 10 cm depth.

the test group that began lactating in 2005, 21 cows were selected using the same methodology described above. In total, 39 cows were selected by the MPFOS and consisted of two groups (2004–07 and 2005–08). As weather conditions vary from year to year, the two groups were also used to test the temporal robustness of the model forecasts. All of the 39 cows selected had four consecutive years of milk production from the first to the fourth lactation, some of which were incomplete lactations (less than 305 days). The DMY of the fourth lactation was chosen for model validation while the first three lactation records were used as model training inputs.

2.2. Model inputs

In this study, DMY, DIM and corresponding daily weather meteorological data (rainfall, sunshine hours and soil temperature) were selected as model inputs. This study focused on forecasts at the individual cow level as opposed to herd level. The inclusion of the meteorological parameters at this level were chosen to preclude forecast aggregation effects that may occur at herd level (averaging of milk production figures between cows). By operating the models at the individual cow level, the impact of adding meteorological parameters to the milk production prediction accuracy for each cow may be investigated while still allowing averaged values to be calculated. Previous studies have proposed that herd DMY can be viewed as a time series that is being driven by DIM and the number of cows milked at the herd level [35]. Similarly, the DMY can be viewed as a time series at the individual cow level as shown in previous studies [36–39]. The DIM was factored in by chronologically applying a day number (1–305) relative to the beginning of calving date for each individual cow. The meteorological data corresponding to each day number was trained in parallel with DIM and DMY.

Multiple combinations of meteorological data were applied and tested along with DIM and DMY as model inputs. The historical milk yield training data were pre-processed using eight treatments designed to factor meteorological data (MD) into the model configuration and training process: #1 standard input (with DIM and DMY only) Eq. (1); #2 including precipitation, Eq. (2); #3 including sunshine hours, Eq. (3); #4 including soil temperature, Eq. (4); #5 including precipitation and sunshine hours, Eq. (5); #6 including precipitation and soil temperature, Eq. (6); #7 including sunshine hours and soil temperature, Eq. (7); #8 including precipitation, sunshine hours and soil temperature, Eq. (8). A summary of weather combination input treatments is shown in Table 2.

#1 standard input

$$Y_{training} = \begin{bmatrix} DMY_1 \\ DMY_2 \\ DMY_3 \end{bmatrix} \tag{1}$$

#2 precipitation

$$Y_{training} = \begin{bmatrix} DMY_1 \\ DMY_2 \\ DMY_3 \end{bmatrix} + \begin{bmatrix} MDP_1 \\ MDP_2 \\ MDP_3 \end{bmatrix} \tag{2}$$

#3 sunshine hours

$$Y_{training} = \begin{bmatrix} DMY_1 \\ DMY_2 \\ DMY_3 \end{bmatrix} + \begin{bmatrix} MDS_1 \\ MDS_2 \\ MDS_3 \end{bmatrix} \tag{3}$$

#4 soil temperature

$$Y_{training} = \begin{bmatrix} DMY_1 \\ DMY_2 \\ DMY_3 \end{bmatrix} + \begin{bmatrix} MDT_1 \\ MDT_2 \\ MDT_3 \end{bmatrix} \tag{4}$$

#5 precipitation and sunshine hours

$$Y_{training} = \begin{bmatrix} DMY_1 \\ DMY_2 \\ DMY_3 \end{bmatrix} + \begin{bmatrix} MDP_1 \\ MDP_2 \\ MDP_3 \end{bmatrix} + \begin{bmatrix} MDS_1 \\ MDS_2 \\ MDS_3 \end{bmatrix} \tag{5}$$

#6 precipitation and soil temperature

$$Y_{training} = \begin{bmatrix} DMY_1 \\ DMY_2 \\ DMY_3 \end{bmatrix} + \begin{bmatrix} MDP_1 \\ MDP_2 \\ MDP_3 \end{bmatrix} + \begin{bmatrix} MDT_1 \\ MDT_2 \\ MDT_3 \end{bmatrix} \tag{6}$$

#7 sunshine hours and soil temperature

$$Y_{training} = \begin{bmatrix} DMY_1 \\ DMY_2 \\ DMY_3 \end{bmatrix} + \begin{bmatrix} MDS_1 \\ MDS_2 \\ MDS_3 \end{bmatrix} + \begin{bmatrix} MDT_1 \\ MDT_2 \\ MDT_3 \end{bmatrix} \tag{7}$$

#8 precipitation, sunshine hours and soil temperature

$$Y_{training} = \begin{bmatrix} DMY_1 \\ DMY_2 \\ DMY_3 \end{bmatrix} + \begin{bmatrix} MDP_1 \\ MDP_2 \\ MDP_3 \end{bmatrix} + \begin{bmatrix} MDS_1 \\ MDS_2 \\ MDS_3 \end{bmatrix} + \begin{bmatrix} MDT_1 \\ MDT_2 \\ MDT_3 \end{bmatrix} \tag{8}$$

Table 2 – Legend of weather combination in input treatments.

Input Treatment	Rainfall	Sunshine hours	Soil Temperature	Short Code
#1	–	–	–	000
#2	Y	–	–	R00
#3	–	Y	–	0S0
#4	–	–	Y	00T
#5	Y	Y	–	RS0
#6	Y	–	Y	R0T
#7	–	Y	Y	0ST
#8	Y	Y	Y	RST

For Eqs. (1)–(8), where DMY_1, DMY_2, DMY_3 is the daily milk yield in the first, second and third lactation, respectively; MDP_1, MDP_2, MDP_3 is the daily precipitation in the first, second and third lactation, respectively; MDS_1, MDS_2, MDS_3 is the daily sunshine hours in the first, second and third lactation, respectively; and MDT_1, MDT_2, MDT_3 is the daily soil temperature in the first, second and third lactation, respectively.

2.3. Model configuration

2.3.1. The regression model

The MLR model has been proposed by multiple authors in cognate studies [23,28,40,41]. The MLR model was chosen in this study for two reasons. Firstly, the MLR model has proved to be successful in milk yield forecasting at the herd level [3,28,29,42]. Secondly, the MLR model can use a greater number of input variables compared to curve fitting models (such as Wood's curve fitting model), which can only incorporate DIM and DMY. The study of Smith [3] successfully demonstrated that adding rainfall and temperature as additional input variables can improve annual milk yield forecasting accuracy of a MLR model. In addition, the results from the previous study of MPFOS using data from Irish dairy farms showed that multiple curve fitting models including the Wood's model did not perform better than the MLR model [32]. Hence in this study, to assess the influence of incorporating additional weather data when forecasting milk yield for the individual cow, the expression of the MLR model (Eq. (9)) used was revised from that originally developed by Murphy et al. [35].

$$Y_t = \varepsilon + \alpha_1 NCM_t + \alpha_2 DIM_t + \alpha_3 MD_{1t} + \alpha_4 MD_{2t} + \cdots + \alpha_M MD_{Nt} \tag{9}$$

where Y_t is the daily milk yield (DMY) and the dependent variable, number of cows milked (NCM), days in milk (DIM) and meteorological data (MD_1 up to MD_N) are independent variables, α_1 up to α_M are the regression coefficients and ε is the residual error.

2.3.2. The auto-regressive model

Previous research by Murphy et al. [35] demonstrated how the NARX model was successful in milk production forecasting at the herd level with training data consisting of herd DMY, DIM and number of cows milked (NCM). In this study, the actual NCM value was either one or zero on each day in the lactation during individual cow simulations, the NCM was adopted in the form of Boolean values to mark if a cow was milked on the corresponding DIM or not. This was introduced to accommodate incomplete lactations (less than 305 days) in the model training process. Meteorological data were introduced as training inputs as the NARX model has the ability of using multiple inputs based on the study of Murphy et al. The NARX model employed neural networks with tapped delay signals, which combined input and output data from recent time steps as embedded short-term memory as well as pattern recognition within the network (detailed architecture of the NARX model can be seen in the study of Murphy et al. and MPFOS [32,35]). Therefore, the NARX model was trained using individual cow DMY as the predicted time series with the DIM, the NCM and meteorological data (MD_1 up to MD_N) as corresponding time series. The most accurate NARX configuration for each cow was calculated by the MPFOS including the number of neurons in the hidden layer, the training function and the transfer function in accordance with the methodology used by Murphy et al. [35]. Tapped delay lines were used to give the model short-term memory. Multiple day delays were trialed (2, 4 and 6 days) so the model could take into account any existing time lags between the meteorological parameters and milk production.

2.3.3. Evaluation criteria

The evaluation criteria were chosen and configured from the MPFOS in accordance with the evaluation methods of cognate studies, including: Summed Square of Residuals (SSE), Coefficient of determination (R^2) and Root Mean Squared Error (RMSE) [28,29,35,43–46]. Based on study of Olori et al. the R^2 value represents a measure of how well observed outcomes are replicated by model forecasts and provides the goodness of fit between the observed values and the actual values, based on the proportion of total variation of outcomes explained by the model. Olori et al. classified model prediction performance as good, fair or poor, if $R^2 \geq 0.7$, $0.7 > R^2 \geq 0.4$, or $R^2 < 0.4$, respectively [47]. Detailed information regarding these statistical criteria is available within Appendix B of the original MPFOS study [32].

In addition, the percentage of difference (POD) was introduced in this study as an indicator of an increase or decrease in prediction accuracy. The POD was calculated as follows:

$$POD = (RMSE_{standard} - RMSE_{control\ group})/RMSE_{standard} \times 100\% \tag{10}$$

where the POD of treatment #2 for each cow was set to 1 as the base line, positive POD values of other input treatments (from treatment #2 to treatment #8) shows that the prediction improved in the form of decreasing (positive) RMSE values. Similarly, a negative POD value of other input treatments shows that the prediction worsened in the form of increasing RMSE values.

3. Results and discussion

3.1. Model comparison

The statistical results of the NARX model and the MLR model forecasts against the validation dataset of 39 individual cows' DMY are shown in Table 5 (see Appendix). According to definitions of model quality based on R^2 from Olori et al. [47], the NARX models can be classified as 'good' (R^2 values greater than 0.70) in 298 of 312 predictions (95.5%, see Table 5). In contrast, the MLR model can only be considered 'good' in 46 out of 312 cases (14.7%, see Table 5). It is clear that the NARX model was more accurate than the MLR model for all 39 cows, based on R^2, RMSE and SSE values (see Fig. 1 and Table 6). These direct outcomes support the hypotheses that the NARX model can provide greater accuracy when predicting milk yield compared to the MLR model at the individual cow level. However, a substantial variation in R^2 values between cows can be seen due to atypical curves of the fourth lactations.

3.2. Effect of different treatments

The RMSE POD values for each of the 39 test cows for all eight treatments (from treatment #1 to treatment #8) is shown in Table 6 (see Appendix). The positive or negative POD values in RMSE show how the treatment predictions improved (positive POD) or worsened (negative POD) in the form of decreasing or increasing RMSE values, respectively. The statistical summary of Table 6 is shown in Table 3.

The average RMSE POD values for 18 cows from the 2004–2007 group is shown in Table 3-1. Seven treatments (#2–#8) applied to the input data of the NARX model slightly improved predictions of 7–15 cows (POD > 0) depending on the treatment. For the single weather parameter inputs, the average POD varied from 1.5% (treatment #2, precipitation) to 4.3% (treatment #3, sunshine hours), which implied decreased RMSE values and improved model forecasting accuracy on average (18 cows). For the dual weather parameter inputs, the average POD varied from 0.2% (treatment #5, precipitation and sunshine hours) to 1.3% (treatment #6, precipitation and soil temperature), which implied that applying a combination of two weather parameters could not provide better model forecasting accuracy than applying single weather parameters for 18 cows from the group 2004–07. The input treatments applied on the MLR model improved predictions for 4–17 cows and the average POD values varied from −0.1% (treatment #2, precipitation) to 3.4% (treatment #7, sunshine hours and soil temperature).

For the 21 cows from the 2005–08 group, a similar pattern was found from the NARX models' predictions (Table 3-2). For the single weather parameter inputs, all three treatments (#2–#4) slightly improved the model forecasting accuracy (10–15 cows) and decreased RMSE values on average (POD > 0). For the dual weather parameter inputs (#5–#7), three treatments slightly improved model forecasting accuracy (10–14 cows). The average POD values were higher, compared with the same treatment in the group 2004–07. However, the triple weather parameter input (treatment #8, precipitation, sunshine hours and soil temperature) only improved predictions for 8 cows with a limited positive average POD (0.7%). The input treatments applied to the MLR model improved predictions for 8–17 cows and the average POD were lower than those of same input treatments (#3–#8) in the group 2004–07.

The average RMSE POD values of the tested models using seven treatments for 39 cows is shown in Table 3-3. Treatment #3 (sunshine hours) had the highest POD value for the NARX model (3.4%). Treatment #7 (sunshine hours and soil temperature) had the highest POD value the MLR model (2.2%). Treatment #8 (precipitation, sunshine hours and soil temperature) had the second highest POD value for the MLR model (2.1%). For the NARX model, the application of single weather parameter inputs (treatment #2, #3, #4, POD varied from 1.8% to 3.4%) were more effective than dual weather parameter inputs (treatment #5 precipitation and sunshine

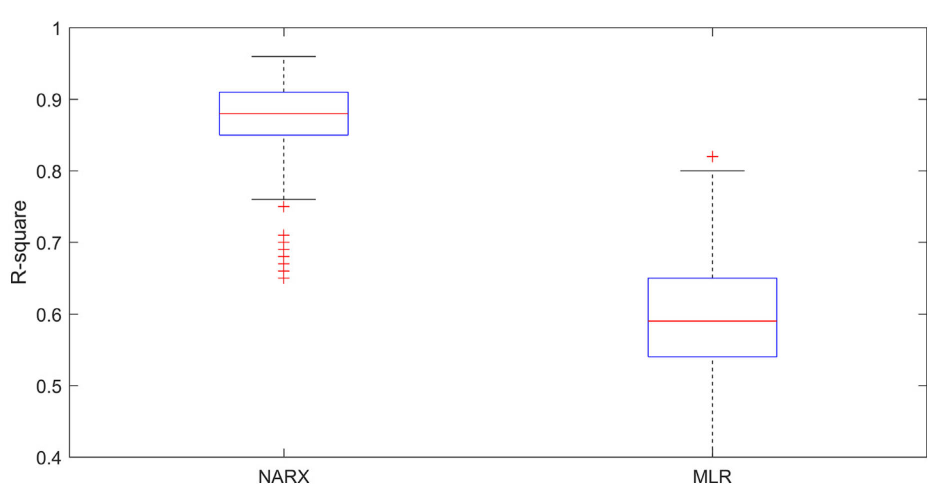

Fig. 1 – Overall R^2 values distribution of predictions of test models for 39 cows using seven weather treatments.

Table 3 – Statistical summary of RMSE percentage of difference (POD) values (NARX and MLR). Positive POD indicates an improvement in prediction.

3–1 Summary of RMSE POD values for cows from year of 2004–2007
18 cows (2004–2007)

Treatment*	NARX		MLR	
	POD*	No. of improved	POD*	No. of improved
#1	1	0	1	0
#2	1.5%	11	−0.1%	4
#3	4.3%	15	2.1%	17
#4	2.4%	13	2.3%	13
#5	0.2%	7	2.0%	17
#6	1.3%	10	2.2%	13
#7	1.2%	8	3.4%	15
#8	1.5%	8	3.2%	15

3–2 Summary of RMSE POD values for cows from year of 2005–2008
21 cows (2005–2008)

Treatment*	NARX		MLR	
	POD*	No. of improved	POD*	No. of improved
#1	1	0	1	0
#2	2.1%	10	−0.1%	8
#3	2.7%	15	0.9%	16
#4	1.5%	12	0.3%	9
#5	2.0%	14	1.3%	17
#6	1.6%	13	0.2%	9
#7	2.1%	10	1.2%	14
#8	0.7%	8	1.1%	14

3–3 Summary of RMSE POD values for overall sample
39 cows (2004–2007, 2005–2008)

Treatment*	NARX		MLR	
	POD*	No. of improved	POD*	No. of improved
#1	1	0	1	0
#2	1.8%	21	−0.1%	12
#3	3.4%	30	1.5%	33
#4	1.9%	25	1.2%	22
#5	1.2%	21	1.7%	34
#6	1.5%	23	1.1%	22
#7	1.7%	18	2.2%	29
#8	1.1%	16	2.1%	29

POD*: average POD of prediction for cows in each treatment.
Treatment*: #1 standard input, #2 precipitation, #3 sunshine hours, #4 soil temperature, #5 precipitation and sunshine hours, #6 precipitation and soil temperature, #7 sunshine hours and soil temperature, #8 precipitation, sunshine hours and soil temperature.

hours, #6 precipitation and soil temperature, #7 sunshine hours and soil temperature, POD varied from 1.2% to 1.7%) or triple treatment weather parameter inputs (treatment #8 precipitation, sunshine hours and soil temperature, POD = 1.1%).

It is clear that including sunshine hours as a model input can improve prediction accuracy more than applying precipitation for the NARX model. The attempt of combining dual and triple weather parameters (from treatment #5 to treatment #8) showed that although average POD values were increased and RMSE were reduced when compared to treatment #1, POD values were not better than treatment #3 (sunshine hours). This finding was unexpected and suggests that sunshine hours but not soil temperature was the most effective weather parameter, compared to previous studies [3].

Although all seven treatments (#2–#8) appeared to produce superior milk production forecasting accuracy in comparison to the original data input methodology (treatment #1) (Table 3-3), the improvements were small in most cases and may have been attributable to noise in the data sets. The improvements due to the addition of sunshine hours were consistent between the groups but the error reduction was still low.

The average RMSE POD values of different prediction horizons of the NARX model using eight treatments for 39 cows is shown in Table 4. Treatment #3 (sunshine hours) delivered the highest POD value in the 10-day and 30-day predictions while treatment #2 (precipitation) delivered the highest POD value in the 305-day prediction.

3.3. General discussion

Based on the results in this study, adding weather parameters as training inputs contributed to only a minor improvement

Table 4 – Statistical summary of RMSE percentage of difference (POD) values (NARX model). Positive POD indicates an improvement in prediction.

4–1 Summary of RMSE POD values for overall sample (18 cows)
18 cows (2004–2007)

	NARX		NARX		NARX		Average
	10-day		30-day		305-day		
Treatment*	POD*	No. of improved	POD*	No. of improved	POD*	No. of improved	
#1	1	0	1	0	1	0	
#2	1.5%	11	1.4%	12	4.4%	13	2.43%
#3	4.3%	14	1.5%	10	2.1%	13	2.63%
#4	2.4%	13	−0.8%	7	−0.3%	9	0.43%
#5	0.2%	8	0.3%	6	2.8%	13	1.10%
#6	1.3%	10	−2.3%	9	−0.3%	9	−0.43%
#7	1.2%	8	0.9%	9	3.5%	15	1.87%
#8	1.5%	8	−1.8%	8	2.4%	12	0.70%

POD*: average POD of prediction for cows in each treatment.

4–2 Summary of RMSE POD values for overall sample (21 cows)
21 cows (2005–2008)

	NARX		NARX		NARX		Average
	10-day		30-day		305-day		
Treatment*	POD*	No. of improved	POD*	No. of improved	POD*	No. of improved	
#1	1	0	1	0	1	0	
#2	2.1%	10	2.0%	11	1.1%	8	1.73%
#3	2.7%	15	4.3%	16	1.3%	6	2.77%
#4	1.5%	12	2.3%	11	2.7%	9	2.17%
#5	2.0%	14	4.1%	15	0.9%	8	2.33%
#6	1.6%	14	2.0%	11	2.1%	8	1.90%
#7	2.1%	10	3.4%	14	1.0%	9	2.17%
#8	0.7%	8	3.1%	15	0.5%	9	1.43%

POD*: average POD of prediction for cows in each treatment.

4–3 Summary of RMSE POD values for overall sample (39 cows)
39 cows (2004–2007, 2005–2008)

	NARX		NARX		NARX		Average
	10-day		30-day		305-day		
Treatment*	POD*	No. of improved	POD*	No. of improved	POD*	No. of improved	
#1	1	0	1	0	1	0	
#2	1.8%	21	1.7%	23	2.6%	21	2.03%
#3	3.4%	29	3.0%	26	1.7%	19	2.70%
#4	1.9%	25	0.9%	18	1.3%	18	1.37%
#5	1.2%	22	2.3%	21	1.8%	21	1.77%
#6	1.5%	24	0.0%	20	1.0%	17	0.83%
#7	1.7%	18	2.2%	23	2.1%	24	2.00%
#8	1.1%	16	0.9%	23	1.4%	21	1.13%

Treatment*: #1 standard input, #2 precipitation, #3 sunshine hours, #4 soil temperature, #5 precipitation and sunshine hours, #6 precipitation and soil temperature, #7 sunshine hours and soil temperature, #8 precipitation, sunshine hours and soil temperature.

in model forecasting accuracy. The statistical results indicated that the inclusion of sunshine hours resulted in the largest improvement in prediction accuracy for all scenarios. However, based on the POD value in this study, the improvement was still low. Although soil temperature has been reported to have a major influence on the grass growth all year around [15], it did not have a substantial impact on milk yield forecasting in this study. Smith et al. [3] employed precipitation and soil temperature to aid in the forecast of milk production. However, their study was based on averaged national level herd data over 50 years ago and the effect on forecast accuracy from the addition of weather parameters to the model was not quantified. The pasture-based management systems during that period were rudimentary and therefore may have been more susceptible to climatic conditions. The cows in this study were all on well managed farms that employed state of the art pasture management practices and technologies. Hence, herbage quantity and quality would have been maintained regardless of ambient conditions. Moreover, concentrate supplementation data were not available which may have been employed in periods of very low grass growth or very wet weather when cows could not graze outdoors. A similar issue was addressed in the study of Roche et al. [6] whereby pasture quality was not allowed to vary greatly resulting in weather variables having only a slight effect on milk production in well-managed modern farms.

This study showed that the introduction of sunshine hours, precipitation and soil temperature data generated a minor improvement on the prediction accuracy of individual cow milk prediction for both models. Compared to the MLR model, the prediction accuracy of the NARX model improved to a greater extent due to additional meteorological input data. This result was consistent with the conclusion of a previous study in Ireland [35], whereby greater forecasting performance was obtained with reduced prediction horizons and error feedback, while the MLR model did not take into account short-term errors, and as a result, limited the potential increase in prediction accuracy [32].

Sunshine hours was found to improve forecast accuracy to the greatest extent, however the overall improvement was still relatively small. Although soil temperature has been reported to have a major influence on the grass growth in Ireland, it did not have a significant impact on milk yield forecasting accuracy within the experimental results. This contrasts with a similar study in the UK in the 1960's [3] where soil temperature was reported to be an effective parameter in the prediction of milk yield. However, these results aligned with the findings of a cognate study in New Zealand [6], where the author suggested that the modern grazing management in the dairy farms prevented cows from lacking feed intake. Milk yield may be affected by both quality and quantity of pasture. Due to the importance of feeding cost for running a commercial dairy farm, the weather factors may only impact grass growth and after that, grazing management factors will control the feeding quality and offset the potential impact of pure natural factors on of dairy farms.

Another limitation of this study was the purely data-driven modelling technique employed, which used only high-level parameters. To effectively factor in the influence weather has on milk production, a more holistic milk forecasting model that takes into account the relationship between grazing conditions, feed intake, farm management and the cows' physiology may be more suitable [13].

4. Conclusions and future work

In this study, the effects of incorporating meteorological factors: precipitation, sunshine hours and soil temperature to milk production forecasting models were tested. Despite varying results between eight different meteorological scenarios, the NARX model was found to provide a greater prediction accuracy than the MLR model for forecasting milk yield at the individual cow level. The statistical results indicate different positive effects of weather factors on milk yield. Based on the POD values in this study, sunshine hours was the most effective weather parameter on average for improving the prediction of cow level milk yield. This result was consistent across model type (MLR and NARX) and prediction horizon (10 day, 30 day and 305 day). However, the overall reduction in error as a result of introducing weather parameters was too small to draw any definitive conclusions regarding the benefits of utilizing weather parameters for milk production forecasting in general. The small reduction in error may be due to modern farm management techniques employed on the dairy farms where the test cows in this study were located. These management techniques reduce the impact that weather variation has on feed intake, which in turn lessens the direct effect that weather has on milk production.

Appendix

Table 5 – Statistical results of the NARX model and the MLR model forecasts using eight treatments for 39 individual cows.

2004–2007	Cow ID	Cow1		Cow2		Cow3	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
#1	RMSE	2.8	2.52	2.52	4.44	2.95	5.86
	SSE	2388	1937	1937	6023	2654	10,490
	R^2	0.93	0.89	0.89	0.67	0.87	0.49
#2	RMSE	2.76	7.23	2.25	4.45	2.69	5.88
	SSE	2326	15,964	1539	6031	2201	10,543
	R^2	0.94	0.56	0.91	0.67	0.89	0.49
#3	RMSE	2.82	6.8	2.3	4.38	2.65	5.63
	SSE	2423	14,117	1619	5855	2135	9670
	R^2	0.93	0.61	0.91	0.68	0.9	0.53
#4	RMSE	2.91	6.9	2.3	4.45	2.84	5.62
	SSE	2584	14,537	1610	6052	2464	9631
	R^2	0.93	0.6	0.91	0.66	0.88	0.53
#5	RMSE	2.83	6.83	2.28	4.39	2.72	5.66
	SSE	2435	14,227	1582	5887	2251	9779
	R^2	0.93	0.61	0.91	0.67	0.89	0.53
#6	RMSE	2.93	6.93	2.31	4.46	2.79	5.63

Table 5 – (continued)

2004–2007	Cow ID	Cow1		Cow2		Cow3	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
	SSE	2617	14,639	1628	6059	2371	9665
	R^2	0.93	0.59	0.91	0.66	0.88	0.53
#7	RMSE	2.88	6.66	2.36	4.39	2.72	5.55
	SSE	2522	13,518	1702	5890	2255	9380
	R^2	0.93	0.63	0.91	0.67	0.89	0.54
#8	RMSE	2.84	6.68	2.29	4.41	2.8	5.58
	SSE	2457	13,622	1596	5923	2393	9494
	R^2	0.93	0.62	0.91	0.67	0.88	0.54
2004–2007	Cow ID	Cow4		Cow5		Cow6	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
#1	RMSE	5.38	8.11	2.66	8.06	3.15	7.1
	SSE	8815	20,043	2163	19,829	3027	15,354
	R^2	0.81	0.58	0.96	0.61	0.89	0.45
#2	RMSE	5.11	8.12	2.83	8.05	3.07	7.1
	SSE	7954	20,105	2443	19,782	2883	15,358
	R^2	0.83	0.58	0.95	0.61	0.9	0.45
#3	RMSE	4.92	7.82	2.57	8.04	3.27	6.87
	SSE	7387	18,656	2010	19,699	3258	14,401
	R^2	0.84	0.61	0.96	0.61	0.88	0.49
#4	RMSE	5	7.37	2.47	8	3.28	7.49
	SSE	7614	16,573	1864	19,522	3281	17,122
	R^2	0.84	0.65	0.96	0.61	0.88	0.39
#5	RMSE	5.05	7.82	2.64	8.04	3.2	6.88
	SSE	7767	18,654	2122	19,695	3115	14,452
	R^2	0.84	0.61	0.96	0.61	0.89	0.48
#6	RMSE	4.7	7.38	2.65	7.98	3.11	7.48
	SSE	6742	16,625	2143	19,435	2951	17,084
	R^2	0.86	0.65	0.96	0.61	0.89	0.39
#7	RMSE	4.81	7.31	2.82	7.87	3.2	7.33
	SSE	7060	16,307	2433	18,881	3127	16,377
	R^2	0.85	0.66	0.95	0.62	0.89	0.42
#8	RMSE	4.9	7.32	2.62	7.87	3.23	7.34
	SSE	7314	16,337	2088	18,895	3185	16,449
	R^2	0.85	0.66	0.96	0.62	0.89	0.41
2004–2007	Cow ID	Cow7		Cow8		Cow9	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
#1	RMSE	5.18	8.17	2.7	5.58	3.97	8.05
	SSE	8180	20,340	2226	9510	4814	19,760
	R^2	0.85	0.64	0.9	0.62	0.9	0.62
#2	RMSE	3.93	8.16	3.15	5.59	4.12	8.05
	SSE	4722	20,329	3036	9536	5184	19,745
	R^2	0.92	0.64	0.88	0.62	0.9	0.62
#3	RMSE	4.01	8	2.79	5.4	3.95	7.78
	SSE	4916	19,525	2373	8909	4758	18,448
	R^2	0.91	0.65	0.91	0.65	0.91	0.65
#4	RMSE	3.81	8.09	2.69	5.7	3.96	7.91
	SSE	4436	19,956	2202	9914	4772	19,061
	R^2	0.92	0.64	0.91	0.61	0.91	0.64
#5	RMSE	4.23	8.01	3.22	5.4	4.07	7.78
	SSE	5446	19,553	3153	8895	5060	18,466
	R^2	0.9	0.65	0.87	0.65	0.9	0.65

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Table 5 – (*continued*)

2004–2007 Cow ID		Cow7		Cow8		Cow9	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
#6	RMSE	3.83	8.09	3.1	5.7	4.19	7.91
	SSE	4482	19,954	2936	9922	5351	19,061
	R^2	0.92	0.64	0.88	0.61	0.9	0.64
#7	RMSE	4.04	7.98	2.68	5.55	4.03	7.72
	SSE	4989	19,434	2197	9393	4953	18,196
	R^2	0.91	0.65	0.91	0.63	0.91	0.65
#8	RMSE	4.02	7.99	2.78	5.55	4.03	7.73
	SSE	4925	19,467	2357	9386	4961	18,219
	R^2	0.91	0.65	0.91	0.63	0.91	0.65
2004–2007 Cow ID		Cow10		Cow11		Cow12	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
#1	RMSE	3.02	6.86	3.61	6.38	2.25	2.53
	SSE	2784	14,341	3982	12,417	1539	1945
	R^2	0.91	0.57	0.93	0.78	0.83	0.79
#2	RMSE	3.18	6.87	3.74	6.4	2.22	2.54
	SSE	3083	14,406	4263	12,475	1499	1967
	R^2	0.91	0.57	0.92	0.78	0.84	0.79
#3	RMSE	2.98	6.74	3.49	6.09	2.2	2.62
	SSE	2711	13,849	3717	11,301	1483	2100
	R^2	0.92	0.59	0.93	0.8	0.84	0.77
#4	RMSE	3.43	6.72	3.44	5.8	2.15	2.55
	SSE	3584	13,794	3616	10,252	1404	1978
	R^2	0.89	0.59	0.94	0.82	0.85	0.79
#5	RMSE	3.13	6.74	3.52	6.06	2.45	2.63
	SSE	2980	13,835	3788	11,213	1838	2102
	R^2	0.91	0.59	0.93	0.8	0.8	0.77
#6	RMSE	3.3	6.74	3.37	5.8	2.41	2.56
	SSE	3323	13,862	3470	10,262	1775	1998
	R^2	0.9	0.59	0.94	0.82	0.81	0.78
#7	RMSE	3.27	6.69	3.53	5.72	2.32	2.63
	SSE	3265	13,667	3804	9993	1643	2105
	R^2	0.9	0.59	0.93	0.82	0.82	0.77
#8	RMSE	3.37	6.69	3.62	5.71	2.47	2.63
	SSE	3471	13,662	3994	9941	1855	2107
	R^2	0.9	0.59	0.93	0.82	0.8	0.77
2004–2007 Cow ID		Cow13		Cow14		Cow15	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
#1	RMSE	2.2	3.37	3.85	5.63	2.84	4.55
	SSE	1472	3462	4522	9654	2466	6317
	R^2	0.88	0.72	0.84	0.65	0.9	0.73
#2	RMSE	2.22	3.37	3.84	5.63	2.66	4.55
	SSE	1504	3463	4492	9675	2159	6323
	R^2	0.88	0.71	0.84	0.65	0.91	0.73
#3	RMSE	2.12	3.31	3.7	5.45	2.51	4.53
	SSE	1365	3337	4179	9072	1918	6249
	R^2	0.89	0.73	0.85	0.67	0.92	0.73
#4	RMSE	2.36	3.34	3.66	4.93	2.66	4.64
	SSE	1700	3394	4076	7412	2163	6579

Table 5 – (continued)

2004–2007	Cow ID	Cow13		Cow14		Cow15	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
	R^2	0.86	0.72	0.85	0.73	0.91	0.72
#5	RMSE	2.17	3.32	3.85	5.45	2.92	4.53
	SSE	1435	3356	4527	9059	2609	6254
	R^2	0.88	0.72	0.84	0.67	0.89	0.73
#6	RMSE	2.32	3.34	3.86	4.93	2.64	4.65
	SSE	1637	3398	4537	7423	2125	6583
	R^2	0.87	0.72	0.84	0.73	0.91	0.72
#7	RMSE	2.33	3.3	3.53	4.9	2.88	4.6
	SSE	1650	3321	3802	7310	2536	6468
	R^2	0.86	0.73	0.86	0.73	0.89	0.73
#8	RMSE	2.31	3.31	3.49	4.9	2.7	4.61
	SSE	1621	3339	3708	7320	2227	6471
	R^2	0.87	0.73	0.87	0.73	0.91	0.73
2004–2007	Cow ID	Cow16		Cow17		Cow18	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
#1	RMSE	2.92	4.72	4.18	4.85	4.15	5.19
	SSE	2599	6797	5339	7182	5244	8220
	R^2	0.88	0.7	0.69	0.59	0.75	0.61
#2	RMSE	2.87	4.73	4.26	4.86	4	5.19
	SSE	2506	6823	5539	7193	4875	8211
	R^2	0.89	0.7	0.68	0.59	0.77	0.61
#3	RMSE	2.89	4.63	4.08	4.81	4.07	5.15
	SSE	2556	6551	5072	7058	5056	8088
	R^2	0.89	0.71	0.71	0.59	0.76	0.61
#4	RMSE	3.02	4.58	4.17	4.7	4.08	5.19
	SSE	2784	6397	5309	6732	5083	8206
	R^2	0.88	0.72	0.69	0.61	0.76	0.61
#5	RMSE	3.01	4.64	4.24	4.82	4.08	5.15
	SSE	2767	6558	5477	7081	5068	8105
	R^2	0.88	0.71	0.68	0.59	0.76	0.61
#6	RMSE	3.04	4.59	4.14	4.7	3.88	5.18
	SSE	2810	6427	5229	6748	4592	8199
	R^2	0.88	0.71	0.7	0.61	0.78	0.61
#7	RMSE	3.08	4.54	4.34	4.69	3.99	5.15
	SSE	2889	6284	5744	6721	4852	8104
	R^2	0.87	0.72	0.67	0.61	0.77	0.61
#8	RMSE	2.95	4.54	4.25	4.7	4.03	5.16
	SSE	2657	6293	5504	6743	4955	8120
	R^2	0.88	0.72	0.68	0.61	0.76	0.61
2005–2008	Cow ID	Cow19		Cow20		Cow21	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
#1	RMSE	2.77	3.71	3.28	7.5	2.48	5.36
	SSE	2339	4196	3276	17,169	1880	8776
	R^2	0.77	0.59	0.9	0.53	0.9	0.59
#2	RMSE	2.78	3.73	3.38	7.51	2.4	5.35
	SSE	2351	4247	3474	17,203	1759	8741
	R^2	0.77	0.58	0.9	0.53	0.92	0.59
#3	RMSE	2.77	3.63	3.34	7.42	2.41	5.31
	SSE	2334	4028	3412	16,787	1777	8605
	R^2	0.77	0.6	0.91	0.54	0.92	0.6
#4	RMSE	2.89	3.66	3.42	7.52	2.4	5.41
	SSE	2554	4089	3564	17,257	1760	8932

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Table 5 – (*continued*)

2005–2008	Cow ID	Cow19		Cow20		Cow21	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
	R^2	0.75	0.6	0.9	0.53	0.92	0.58
#5	RMSE	2.74	3.64	3.47	7.42	2.41	5.31
	SSE	2292	4038	3669	16,812	1767	8606
	R^2	0.77	0.6	0.9	0.54	0.92	0.59
#6	RMSE	2.88	3.68	3.51	7.53	2.4	5.4
	SSE	2530	4140	3748	17,271	1754	8910
	R^2	0.75	0.59	0.9	0.53	0.92	0.58
#7	RMSE	2.79	3.64	3.38	7.44	2.4	5.34
	SSE	2367	4048	3483	16,876	1763	8709
	R^2	0.77	0.6	0.9	0.54	0.92	0.59
#8	RMSE	2.79	3.65	3.52	7.44	2.41	5.35
	SSE	2379	4057	3785	16,901	1770	8715
	R^2	0.77	0.6	0.9	0.54	0.92	0.59
2005–2008	Cow ID	Cow22		Cow23		Cow24	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
#1	RMSE	2.64	5.95	2.25	5.18	3.69	6.27
	SSE	2122	10,813	1546	8190	4157	11,991
	R^2	0.89	0.46	0.94	0.66	0.83	0.57
#2	RMSE	2.71	6.01	2.37	5.17	2.1	6.24
	SSE	2238	11,011	1708	8147	1350	11,895
	R^2	0.89	0.45	0.93	0.67	0.95	0.57
#3	RMSE	2.79	6.04	2.16	5.12	2.17	6.33
	SSE	2368	11,138	1423	8010	1436	12,202
	R^2	0.88	0.44	0.94	0.67	0.95	0.56
#4	RMSE	2.78	5.99	2.24	5.12	2.23	6.5
	SSE	2355	10,951	1527	7989	1514	12,886
	R^2	0.88	0.45	0.94	0.67	0.95	0.54
#5	RMSE	2.8	6.06	2.22	5.12	2.14	6.32
	SSE	2390	11,200	1507	8010	1401	12,186
	R^2	0.88	0.44	0.94	0.67	0.95	0.56
#6	RMSE	2.81	6.04	2.25	5.1	2.2	6.47
	SSE	2415	11,118	1547	7936	1480	12,750
	R^2	0.88	0.44	0.94	0.67	0.95	0.54
#7	RMSE	2.94	6.07	2.24	4.98	2.17	6.44
	SSE	2628	11,243	1526	7579	1430	12,649
	R^2	0.87	0.43	0.94	0.69	0.95	0.55
#8	RMSE	2.89	6.09	2.35	4.99	2.31	6.44
	SSE	2547	11,304	1680	7584	1625	12,633
	R^2	0.87	0.43	0.93	0.69	0.94	0.55
2005–2008	Cow ID	Cow25		Cow26		Cow27	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
#1	RMSE	3.13	6.35	3.61	5.59	2.45	6.81
	SSE	2988	12,317	3966	9522	1835	14,162
	R^2	0.88	0.51	0.82	0.59	0.94	0.51
#2	RMSE	3.01	6.36	3.23	5.58	2.6	6.81
	SSE	2768	12,334	3187	9503	2068	14,147
	R^2	0.89	0.51	0.86	0.59	0.93	0.51
#3	RMSE	3.12	6.21	3.27	5.55	2.64	6.52
	SSE	2974	11,744	3252	9403	2128	12,955
	R^2	0.88	0.54	0.86	0.6	0.93	0.55
#4	RMSE	3.22	5.89	3.19	5.64	2.89	6.84
	SSE	3165	10,574	3102	9715	2553	14,275
	R^2	0.88	0.58	0.87	0.59	0.91	0.51
#5	RMSE	3.06	6.2	3.18	5.56	2.7	6.52

Table 5 – (*continued*)

2005–2008	Cow ID	Cow25		Cow26		Cow27	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
	SSE	2857	11,739	3090	9421	2223	12,957
	R^2	0.89	0.54	0.87	0.6	0.92	0.55
#6	RMSE	3.12	5.9	3.12	5.64	2.81	6.84
	SSE	2963	10,609	2969	9691	2416	14,257
	R^2	0.88	0.58	0.87	0.59	0.92	0.51
#7	RMSE	3.28	5.79	3.18	5.6	2.86	6.54
	SSE	3283	10,217	3089	9571	2498	13,032
	R^2	0.87	0.6	0.87	0.59	0.91	0.55
#8	RMSE	3.23	5.8	3.08	5.61	2.85	6.54
	SSE	3182	10,272	2900	9585	2479	13,029
	R^2	0.87	0.6	0.88	0.59	0.91	0.55
2005–2008	Cow ID	Cow28		Cow29		Cow30	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
#1	RMSE	3.24	5.84	5.41	7.38	3.01	3.01
	SSE	3197	10,412	8918	16,606	2767	2767
	R^2	0.85	0.52	0.79	0.62	0.87	0.87
#2	RMSE	3.33	5.89	5.39	7.4	2.94	5.19
	SSE	3392	10,582	8861	16,691	2637	8203
	R^2	0.85	0.52	0.8	0.61	0.88	0.61
#3	RMSE	3.27	5.9	5.32	7.4	3.01	5.1
	SSE	3266	10,600	8635	16,694	2758	7919
	R^2	0.85	0.52	0.8	0.61	0.87	0.63
#4	RMSE	3.31	5.97	5.43	7.23	2.98	5.13
	SSE	3350	10,885	8996	15,933	2712	8012
	R^2	0.85	0.5	0.79	0.63	0.87	0.62
#5	RMSE	3.32	5.4	5.41	7.39	2.94	5.1
	SSE	3359	8895	8928	16,651	2637	7942
	R^2	0.85	0.65	0.79	0.62	0.88	0.62
#6	RMSE	3.3	6	5.47	7.24	3.01	5.13
	SSE	3331	10,996	9125	16,004	2755	8042
	R^2	0.85	0.5	0.79	0.63	0.87	0.62
#7	RMSE	3.38	5.96	5.51	7.3	3.05	5.08
	SSE	3485	10,825	9273	16,248	2829	7880
	R^2	0.84	0.51	0.79	0.63	0.87	0.63
#8	RMSE	3.41	5.96	5.5	7.29	3.06	5.09
	SSE	3545	10,849	9230	16,216	2854	7901
	R^2	0.84	0.5	0.79	0.63	0.87	0.63
2005–2008	Cow ID	Cow31		Cow32		Cow33	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
#1	RMSE	3.02	6.27	2.59	6.09	3.38	6.18
	SSE	2783	11,991	2041	11,305	3486	11,666
	R^2	0.86	0.39	0.9	0.47	0.85	0.49
#2	RMSE	2.89	6.25	2.73	6.09	3.44	6.19
	SSE	2541	11,908	2275	11,308	3600	11,689
	R^2	0.87	0.4	0.89	0.47	0.84	0.49
#3	RMSE	2.92	6.15	2.6	6.1	3.37	6.13
	SSE	2598	11,538	2063	11,339	3470	11,477
	R^2	0.87	0.42	0.9	0.47	0.85	0.49
#4	RMSE	2.99	6.33	2.5	6.29	3.35	6.23

(*continued on next page*)

Table 5 – (*continued*)

2005–2008	Cow ID	Cow31		Cow32		Cow33	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
	SSE	2728	12,236	1904	12,058	3414	11,844
	R^2	0.86	0.38	0.91	0.44	0.85	0.48
#5	RMSE	2.98	6.15	2.72	6.1	3.37	6.13
	SSE	2708	11,537	2250	11,346	3456	11,478
	R^2	0.86	0.42	0.9	0.47	0.85	0.49
#6	RMSE	2.99	6.31	2.56	6.28	3.38	6.23
	SSE	2718	12,140	2001	12,031	3485	11,854
	R^2	0.86	0.39	0.91	0.44	0.85	0.48
#7	RMSE	3.01	6.19	2.62	6.24	3.26	6.2
	SSE	2759	11,687	2090	11,890	3240	11,708
	R^2	0.86	0.41	0.9	0.45	0.86	0.48
#8	RMSE	3.07	6.19	2.57	6.25	3.3	6.2
	SSE	2867	11,688	2018	11,897	3321	11,712
	R^2	0.86	0.41	0.91	0.45	0.85	0.48
2005–2008	Cow ID	Cow34		Cow35		Cow36	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
#1	RMSE	3.56	6.76	3.9	6.53	2.71	5.57
	SSE	3876	13,953	4636	12,994	2247	9476
	R^2	0.88	0.57	0.85	0.57	0.9	0.58
#2	RMSE	3.51	6.76	3.99	6.53	2.76	5.58
	SSE	3764	13,946	4866	13,005	2328	9486
	R^2	0.88	0.57	0.84	0.57	0.9	0.58
#3	RMSE	3.37	6.64	3.88	6.43	2.85	5.53
	SSE	3464	13,435	4594	12,619	2485	9335
	R^2	0.89	0.58	0.85	0.58	0.89	0.59
#4	RMSE	3.48	6.79	3.89	6.42	2.81	5.5
	SSE	3693	14,075	4615	12,586	2403	9228
	R^2	0.89	0.56	0.85	0.58	0.89	0.59
#5	RMSE	3.48	6.64	3.86	6.43	2.85	5.53
	SSE	3694	13,435	4549	12,600	2472	9328
	R^2	0.89	0.58	0.85	0.58	0.89	0.59
#6	RMSE	3.55	6.79	3.81	6.43	2.88	5.5
	SSE	3848	14,052	4423	12,593	2528	9233
	R^2	0.88	0.56	0.85	0.58	0.89	0.59
#7	RMSE	3.54	6.67	3.79	6.37	2.89	5.48
	SSE	3829	13,589	4379	12,385	2545	9160
	R^2	0.88	0.58	0.86	0.59	0.89	0.59
#8	RMSE	3.45	6.68	3.94	6.37	2.82	5.48
	SSE	3633	13,598	4726	12,380	2418	9158
	R^2	0.89	0.58	0.84	0.59	0.89	0.59
2005–2008	Cow ID	Cow37		Cow38		Cow39	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
#1	RMSE	4.25	6.13	3.65	5.08	4.69	6.51
	SSE	5509	11,457	4070	7861	6698	12,943
	R^2	0.79	0.57	0.77	0.56	0.67	0.36
#2	RMSE	4.17	6.13	3.49	5.08	4.72	6.51
	SSE	5291	11,473	3713	7865	6783	12,944
	R^2	0.8	0.57	0.79	0.56	0.66	0.36
#3	RMSE	4.03	6.11	3.54	5	4.64	6.46
	SSE	4952	11,368	3812	7634	6572	12,712

Table 5 – (continued)

2005–2008	Cow ID	Cow37		Cow38		Cow39	
Model		NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	Statistical						
	R^2	0.81	0.57	0.79	0.58	0.67	0.37
#4	RMSE	4.02	6.15	3.47	4.96	4.78	6.36
	SSE	4940	11,536	3680	7505	6969	12,351
	R^2	0.81	0.57	0.8	0.58	0.65	0.39
#5	RMSE	4.15	6.11	3.46	5	4.68	6.44
	SSE	5258	11,395	3657	7635	6683	12,657
	R^2	0.8	0.57	0.8	0.58	0.67	0.37
#6	RMSE	3.97	6.16	3.57	4.96	4.56	6.36
	SSE	4810	11,558	3877	7513	6330	12,350
	R^2	0.82	0.56	0.79	0.58	0.69	0.39
#7	RMSE	3.29	6.13	3.36	4.93	4.71	6.35
	SSE	3292	11,458	3440	7408	6752	12,290
	R^2	0.88	0.57	0.81	0.59	0.66	0.39
#8	RMSE	3.88	6.14	3.58	4.93	4.72	6.34
	SSE	4584	11,482	3904	7414	6802	12,259
	R^2	0.83	0.57	0.78	0.59	0.66	0.39

Treatment*: #1 standard input, #2 precipitation, #3 sunshine hours, #4 soil temperature, #5 precipitation and sunshine hours, #6 precipitation and soil temperature, #7 sunshine hours and soil temperature, #8 precipitation, sunshine hours and soil temperature.

Table 6 – POD (Percentage of difference) in RMSE of the NARX model and the MLR model forecasts using eight treatments for 39 individual cows.

2004–2007	Cow1		Cow2		Cow3		Cow4		Cow5	
	NARX	MLR	NARX	MLR	NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	10	10	10	10	10	10	10	10	10	10
#1	1	1	1	1	1	1	1	1	1	1
#2	1.3%	−0.3%	10.8%	−0.1%	8.9%	−0.3%	5.0%	−0.2%	−6.3%	0.1%
#3	−0.7%	5.7%	8.6%	1.4%	10.3%	4.0%	8.5%	3.5%	3.6%	0.3%
#4	−4.0%	4.3%	8.8%	−0.2%	3.6%	4.2%	7.1%	9.1%	7.1%	0.8%
#5	−1.0%	5.3%	9.6%	1.1%	7.9%	3.4%	6.1%	3.5%	0.9%	0.3%
#6	−4.7%	4.0%	8.3%	−0.3%	5.5%	4.0%	12.5%	8.9%	0.5%	1.0%
#7	−2.8%	7.7%	6.3%	1.1%	7.8%	5.4%	10.5%	9.8%	−6.1%	2.4%
#8	−1.4%	7.4%	9.2%	0.8%	5.0%	4.9%	8.9%	9.7%	1.7%	2.4%
2004–2007	Cow6		Cow7		Cow8		Cow9		Cow10	
	NARX	MLR	NARX	MLR	NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	10	10	10	10	10	10	10	10	10	10
#1	1	1	1	1	1	1	1	1	1	1
#2	2.4%	0.0%	24.0%	0.0%	−16.8%	−0.1%	−3.8%	0.0%	−5.3%	−0.2%
#3	−3.7%	3.2%	22.5%	2.0%	−3.2%	3.2%	0.6%	3.4%	1.3%	1.7%
#4	−4.1%	−5.6%	26.4%	0.9%	0.6%	−2.1%	0.4%	1.8%	−13.5%	1.9%
#5	−1.4%	3.0%	18.4%	2.0%	−19.0%	3.3%	−2.5%	3.3%	−3.5%	1.8%
#6	1.3%	−5.5%	26.0%	1.0%	−14.8%	−2.1%	−5.4%	1.8%	−9.3%	1.7%
#7	−1.6%	−3.3%	21.9%	2.3%	0.7%	0.6%	−1.4%	4.0%	−8.3%	2.4%
#8	−2.6%	−3.5%	22.4%	2.2%	−2.9%	0.7%	−1.5%	4.0%	−11.7%	2.4%
2004–2007	Cow11		Cow12		Cow13		Cow14		Cow15	
	NARX	MLR	NARX	MLR	NARX	MLR	NARX	MLR	NARX	MLR
	10	10	10	10	10	10	10	10	10	10
Treatment*	1	1	1	1	1	1	1	1	1	1
#1	−3.5%	−0.2%	1.3%	−0.6%	−1.1%	0.0%	0.3%	−0.1%	6.4%	0.0%
#2	3.4%	4.6%	1.9%	−3.9%	3.7%	1.8%	3.9%	3.1%	11.8%	0.5%
#3	4.7%	9.1%	4.5%	−0.8%	−7.5%	1.0%	5.1%	12.4%	6.3%	−2.1%
#4	2.5%	5.0%	−9.3%	−4.0%	1.3%	1.5%	−0.1%	3.1%	−2.9%	0.5%
#5	6.6%	9.1%	−7.4%	−1.4%	−5.5%	0.9%	−0.2%	12.3%	7.2%	−2.1%
#6	2.3%	10.3%	−3.3%	−4.0%	−5.9%	2.1%	8.3%	13.0%	−1.4%	−1.2%
#7	−0.2%	10.5%	−9.8%	−4.1%	−4.9%	1.8%	9.5%	12.9%	5.0%	−1.2%

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Table 6 – (continued)

2004–2007	Cow16		Cow17		Cow18					
	NARX	MLR	NARX	MLR	NARX	MLR				
Treatment*	10	10	10	10	10	10				
#1	1	1	1	1	1	1				
#2	1.8%	−0.2%	−1.9%	−0.1%	3.6%	0.1%				
#3	0.8%	1.8%	2.5%	0.9%	1.8%	0.8%				
#4	−3.5%	3.0%	0.3%	3.2%	1.5%	0.1%				
#5	−3.2%	1.8%	−1.3%	0.7%	1.7%	0.7%				
#6	−4.0%	2.8%	1.0%	3.1%	6.4%	0.1%				
#7	−5.4%	3.8%	−3.7%	3.3%	3.8%	0.7%				
#8	−1.1%	3.8%	−1.5%	3.1%	2.8%	0.6%				
2005–2008	Cow19		Cow20		Cow21		Cow22		Cow23	
	NARX	MLR	NARX	MLR	NARX	MLR	NARX	MLR	NARX	MLR
	10	10	10	10	10	10	10	10	10	10
Treatment*	1	1	1	1	1	1	1	1	1	1
#1	−0.3%	−0.6%	−3.0%	−0.1%	3.3%	0.2%	−2.7%	−0.9%	−5.1%	0.3%
#2	0.1%	2.0%	−2.1%	1.1%	2.8%	1.0%	−5.6%	−1.5%	4.1%	1.1%
#3	−4.5%	1.3%	−4.3%	−0.3%	3.2%	−0.9%	−5.4%	−0.6%	0.6%	1.2%
#4	1.0%	1.9%	−5.8%	1.0%	3.1%	1.0%	−6.1%	−1.8%	1.3%	1.1%
#5	−4.0%	0.7%	−7.0%	−0.3%	3.4%	−0.8%	−6.7%	−1.4%	0.0%	1.6%
#6	−0.6%	1.8%	−3.1%	0.9%	3.2%	0.4%	−11.3%	−2.0%	0.7%	3.8%
#7	−0.8%	1.7%	−7.5%	0.8%	3.0%	0.3%	−9.6%	−2.2%	−4.2%	3.8%
2005–2008	Cow24		Cow25		Cow26		Cow27		Cow28	
	NARX	MLR	NARX	MLR	NARX	MLR	NARX	MLR	NARX	MLR
	10	10	10	10	10	10	10	10	10	10
Treatment*	1	1	1	1	1	1	1	1	1	1
#1	43.0%	0.4%	3.8%	−0.1%	10.4%	0.1%	−6.1%	0.1%	−3.0%	−0.8%
#2	41.2%	−0.9%	0.2%	2.4%	9.5%	0.6%	−7.7%	4.4%	−1.1%	−0.9%
#3	39.6%	−3.7%	−2.9%	7.3%	11.6%	−1.0%	−17.9%	−0.4%	−2.4%	−2.2%
#4	41.9%	−0.8%	2.2%	2.4%	11.7%	0.5%	−10.1%	4.3%	−2.5%	7.6%
#5	40.3%	−3.1%	0.4%	7.2%	13.5%	−0.9%	−14.7%	−0.3%	−2.1%	−2.8%
#6	41.3%	−2.7%	−4.8%	8.9%	11.7%	−0.3%	−16.7%	4.1%	−4.4%	−2.0%
#7	37.5%	−2.6%	−3.2%	8.7%	14.5%	−0.3%	−16.2%	4.1%	−5.3%	−2.1%
2005–2008	Cow29		Cow30		Cow31		Cow32		Cow33	
	NARX	MLR	NARX	MLR	NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	10	10	10	10	10	10	10	10	10	10
#1	1	1	1	1	1	1	1	1	1	1
#2	0.3%	−0.3%	2.4%	−0.3%	4.4%	0.3%	−5.6%	0.0%	−1.6%	−0.1%
#3	1.6%	−0.3%	0.2%	1.5%	3.4%	1.9%	−0.5%	−0.1%	0.2%	0.8%
#4	−0.4%	2.0%	1.0%	0.9%	1.0%	−1.0%	3.4%	−3.3%	1.0%	−0.8%
#5	−0.1%	−0.1%	2.4%	1.3%	1.3%	1.9%	−5.0%	−0.2%	0.4%	0.8%
#6	−1.2%	1.8%	0.2%	0.7%	1.2%	−0.6%	1.0%	−3.2%	0.0%	−0.8%
#7	−2.0%	1.1%	−1.1%	1.7%	0.4%	1.3%	−1.2%	−2.6%	3.6%	−0.2%
#8	−1.7%	1.2%	−1.6%	1.6%	−1.5%	1.3%	0.6%	−2.6%	2.4%	−0.2%
2005–2008	Cow34		Cow35		Cow36		Cow37		Cow38	
	NARX	MLR	NARX	MLR	NARX	MLR	NARX	MLR	NARX	MLR
Treatment*	10	10	10	10	10	10	10	10	10	10
#1	1	1	1	1	1	1	1	1	1	1
#2	1.5%	0.0%	−2.5%	0.0%	−1.8%	−0.1%	2.0%	−0.1%	4.5%	0.0%
#3	5.5%	1.9%	0.5%	1.5%	−5.2%	0.7%	5.2%	0.4%	3.2%	1.5%
#4	2.4%	−0.4%	0.2%	1.6%	−3.4%	1.3%	5.3%	−0.3%	4.9%	2.3%
#5	2.4%	1.9%	0.9%	1.5%	−4.9%	0.8%	2.3%	0.3%	5.2%	1.4%
#6	0.4%	−0.4%	2.3%	1.6%	−6.1%	1.3%	6.6%	−0.4%	2.4%	2.2%
#7	0.6%	1.3%	2.8%	2.4%	−6.4%	1.7%	22.7%	0.0%	8.1%	2.9%
#8	3.2%	1.3%	−1.0%	2.4%	−3.7%	1.7%	8.8%	−0.1%	2.1%	2.9%

Table 6 – (*continued*)

2005–2008	Cow39	
	NARX	MLR
Treatment*	10	10
#1	1	1
#2	−0.6%	0.0%
#3	0.9%	0.9%
#4	−2.0%	2.3%
#5	0.1%	1.1%
#6	2.8%	2.3%
#7	−0.4%	2.6%
#8	−0.8%	2.7%

Treatment*: #1 standard input, #2 precipitation, #3 sunshine hours, #4 soil temperature, #5 precipitation and sunshine hours, #6 precipitation and soil temperature, #7 sunshine hours and soil temperature, #8 precipitation, sunshine hours and soil temperature.

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