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#### Identification of the most impacting environmental variables on dairy cow's milk yield using Machine Learning methods

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## Introduction

- Several reports show that the effects of climate change are tangible for different aspects of life on earth (e.g., World Health Organization, National Oceanic and Atmospheric Administration, Intergovernmental Panel on Climate Change)
- Such effects are particularly true for the food production sector, in terms of economic losses and decreases in food quality (Unanaonwi, 2014; Maulu et al., 2021; Singh et al., 2021; Chandio et al., 2022)
- Plus, the effects of climate change are well-documented for milk production (Sheik et al., 2017; Cheng et al., 2022)



# The effects of climate change on milk production

Literature shows that environmental changes can lead to:

#### • Reductions in milk yield

- Reduction in milk quality: fat and protein content
- Poorer cows' health: higher somatic cell counts during heat-stress conditions: somatic cell counts are used as a proxy of animal health

(e.g., Nasr & El-Tarabany, 2017; Sheik et al., 2017; Cheng et al., 2022; Toghdory et al., 2022)

## Our research question

- The short term effects of the climate on milk yield and production has been reported in literature (Biswal et al., 2019)
- It is not well-known the individual impact of the climatic variables and how quickly these climatic conditions can affect milk production and quality.

• We developed a Machine Learning pipeline to identify the most important climatic variables that may influence milk yield and quality and their longterm effect

- The "**production**" dataset: dairy cows' records from 1990 to 2020 (AIA, ANAPRI, LEO Project)
- The "<u>climatic</u>" dataset: daily meteorological information from 1990 to 2020 (downloaded from HL and CMCC's DDS )





- "<u>Production</u>" dataset variables:
  - milk yield
  - fat
  - protein
  - SCC (Somatic Cells Count)
  - date of functional control (FC)
  - latitude and longitude of the farm
  - EBV
  - Parity numbers
  - Farm ID / Animal ID
  - Days in Milk
- Data were quality checked and filtered
- d





- "<u>Climatic</u>" dataset variables:
  - date of the measurement
  - latitude and longitude
  - Temperature (min, max, mean)
  - Relative humidity (min, max, mean)
  - Wind
  - Precipitation (total)
  - Cloud cover (total)
  - Discomfort Index (min, max, cumulated)



## Methods Data and plan of analysis

- The production and climatic data were paired
- The production of each animal was paired with the climatic variables assessed for up to 30 days before the functional control date







## Methods Data and plan of analysis

Pilot dataset: farms located in Friuli-Venezia-Giulia

- The number of FC analyzed in the Machine Learning approach to detect the best prediction model were:
  - **2,332,083** FC (1375 farms \* 105,285 animals)
- The total number of climatic variables analyzed is:
  - 198
- Given the high amount of data and dimensions, we applied a Machine Learning (ML) approach to identify the best climatic variables affecting milk production.



## Methods Our pipeline













×÷ 2 3 5 1 4 **Remove collinear Identify the best Optimize the Evaluate the Explain how each** variable can affect climatic variables algorithm family parameters of the importance of all best algorithm to variables to subset milk production to maintain the to use climatic most informative variables as milk increase its the most and quality ones before data production important accuracy predictors analysis

Climate variables

**Features** 

Targets

Milk yield / quality / SCC

Feature	Agorithm	Proxy	Root Mean Square Error	Mean Absolute Error	R-squared	Range
Milk yield	Random Forest	Production	3.90	2.91	0.06	[-32.93, +32.55]
SCC	XGBoost	Health	0.45	0.34	0.20	[-2.33, +2.70]
Protein	Gradient Boosting Machine	Milk quality	0.20	0.15	0.22	[-1.89, +2.77]
Fat	Gradient Boosting Machine	Milk quality	0.20	0.14	0.20	[-3.79, +3.32]

- Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are used to predict the model accuracy
- They provides an estimate of the typical magnitude of prediction errors. Lower values indicate better model performance

Protein %



• For each of the four phenotypic traits, the most important variables in determining the predictive model were identified using the SHAP (SHapley Additive exPlanations) algorithm

Protein %



 Among the most important variables in explaining the prediction, <u>data from days well before the functional check are found</u>. <u>This suggests</u> <u>a potential long-term effect on milk production and quality</u>



- Several days emerged as important for each feature: 1, 2, 25 and 29 days before the Functional Control
- Some dates were specific for each variable, such as, for example, day 10, 16, 18, 25 and 26 for Proteins



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## Conclusion

- We have developed a <u>machine learning model</u> that allows us to predict milk production data, quality indicators (protein and fat), and somatic cell count based on environmental data
- The model highlights the <u>long-term</u> effects that climatic variables can have on these parameters, while also emphasizing the <u>short-term</u> effects as previously reported (Biswal et al., 2019)
- Furthermore, the model enables the identification not only of the important variables but also of the specific days of interest
- These data can be used to construct more complex models and build <u>risk maps for specific areas or seasons</u>

## Take-home message



Extending the model to different dairy cattle breeds to test specieslevel resilience with varying capacities to adapt to climate change



Optimizing the predictive model on specific areas (e.g. Italian regions) and developing risk maps for the upcoming years



Generating risk maps that can be useful for prediction and provide farmers with the ability to make proactive decisions







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Spoke 5: Sustainable productivity and mitigation of environmental impact in livestock systems





Ente selezionatore

Associazione Nazionale Allevatori Pezzata Rossa Italiana

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$ \subset $		$\mathbf{M}$



Livestock Environment Opendata

Livestock Enviroment OpenData Project https://opendata.leo-italy.eu/portale/home





## Highlander

High performance computing to support smart land services

https://highlanderproject.eu/

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## Methods Collinear variables

- Prior Feature Selection
- Collinear variables were removed
- Only the most important and less informative features were maintained
- 50 variables were selected for temperature, humidity index and wind speed
- 50 variables were selected for Discomfort Index

										H	eat_Ma	р Т_М4	АX									
T_MAX_mean_day_less_1	1	0.97	0.95	0.93	0.92	0.91	0.9	0.9	0.89	0.88	0.88	0.88	0.87	0.87	0.86	0.86	0.85	0.85	0.84	0.84	0.83	0.82
T_MAX_mean_day_less_2	0.97	1	0.97	0.95	0.93	0.92	0.91	0.9	0.9	0.89	0.89	0.88	0.87	0.87	0.86	0.86	0.86	0.85	0.85	0.84	0.83	0.83
T_MAX_mean_day_less_3	0.95	0.97	1	0.97	0.95	0.93	0.92	0.91	0.9	0.9	0.89	0.89	0.88	0.87	0.87	0.86	0.86	0.86	0.86	0.85	0.84	0.84
T_MAX_mean_day_less_4	0.93	0.95	0.97	1	0.97		0.93	0.92	0.91	0.9	0.9	0.89	0.88	0.88	0.87	0.87	0.87	0.86	0.86	0.85	0.85	0.84
T_MAX_mean_day_less_5	0.92	0.93	0.95	0.97	1	0.97		0.93	0.92	0.91	0.9	0.9	0.89	0.88	0.88	0.87	0.87	0.87	0.86	0.86	0.85	0.85
T_MAX_mean_day_less_6	0.91	0.92	0.93	0.95	0.97	1	0.97		0.94	0.92	0.91	0.91	0.9	0.89	0.89	0.88	0.88	0.87	0.87	0.86	0.86	0.85
T_MAX_mean_day_less_7	0.9	0.91	0.92	0.93	0.95	0.97	1	0.97	0.95	0.94	0.92	0.91	0.91	0.9	0.89	0.89	0.88	0.88	0.87	0.87	0.86	0.86
T_MAX_mean_day_less_8	0.9	0.9	0.91	0.92	0.93	0.95	0.97	1	0.97	0.95	0.93	0.92	0.91	0.9	0.9	0.89	0.89	0.88	0.88	0.87	0.86	0.86
T_MAX_mean_day_less_9	0.89	0.9	0.9	0.91	0.92	0.94	0.95	0.97	1	0.97	0.95	0.93	0.92	0.91	0.9	0.9	0.89	0.89	0.88	0.87	0.87	0.86
T_MAX_mean_day_less_10	0.88	0.89	0.9	0.9	0.91	0.92	0.94	0.95	0.97	1	0.97	0.95	0.93	0.92	0.91	0.9	0.9	0.89	0.89	0.88	0.87	0.87
T_MAX_mean_day_less_11	0.88	0.89	0.89	0.9	0.9	0.91	0.92	0.93	0.95	0.97	1	0.97	0.95	0.93	0.92	0.91	0.9	0.9	0.89	0.88	0.88	0.87
T_MAX_mean_day_less_12	0.88	0.88	0.89	0.89	0.9	0.91	0.91	0.92	0.93	0.95	0.97	1	0.97	0.95	0.93	0.92	0.91	0.9	0.9	0.89	0.88	0.88
T_MAX_mean_day_less_13	0.87	0.87	0.88	0.88	0.89	0.9	0.91	0.91	0.92	0.93	0.95	0.97	1	0.97	0.95	0.93	0.92	0.91	0.91	0.9	0.89	0.89
T_MAX_mean_day_less_14	0.87	0.87	0.87	0.88	0.88	0.89	0.9	0.9	0.91	0.92	0.93	0.95	0.97	1	0.97	0.95	0.94	0.92	0.91	0.91	0.9	0.89
T_MAX_mean_day_less_15	0.86	0.86	0.87	0.87	0.88	0.89	0.89	0.9	0.9	0.91	0.92	0.93	0.95	0.97	1	0.97	0.95	0.93	0.92	0.91	0.91	0.9
T_MAX_mean_day_less_16	0.86	0.86	0.86	0.87	0.87	0.88	0.89	0.89	0.9	0.9	0.91	0.92	0.93	0.95	0.97	1	0.97	0.95	0.93	0.92	0.91	0.9
T_MAX_mean_day_less_17	0.85	0.86	0.86	0.87	0.87	0.88	0.88	0.89	0.89	0.9	0.9	0.91	0.92	0.94	0.95	0.97	1	0.97	0.95	0.93	0.92	0.91
T_MAX_mean_day_less_18	0.85	0.85	0.86	0.86	0.87	0.87	0.88	0.88	0.89	0.89	0.9	0.9	0.91	0.92	0.93	0.95	0.97	1	0.97	0.95	0.93	0.92
T_MAX_mean_day_less_19	0.84	0.85	0.86	0.86	0.86	0.87	0.87	0.88	0.88	0.89	0.89	0.9	0.91	0.91	0.92	0.93	0.95	0.97	1	0.97	0.95	
T_MAX_mean_day_less_20	0.84	0.84	0.85	0.85	0.86	0.86	0.87	0.87	0.87	0.88	0.88	0.89	0.9	0.91	0.91	0.92	0.93	0.95	0.97	1	0.97	
T_MAX_mean_day_less_21	0.83	0.83	0.84	0.85	0.85	0.86	0.86	0.86	0.87	0.87	0.88	0.88	0.89	0.9	0.91	0.91	0.92	0.93	0.95	0.97	1	0.97
T_MAX_mean_day_less_22	0.82	0.83	0.84	0.84	0.85	0.85	0.86	0.86	0.86	0.87	0.87	0.88	0.89	0.89	0.9	0.9	0.91	0.92	0.93	0.95	0.97	1
	less_l	less_2	less 3	less 4	less_5	less_6	less_7	less_8	less_9	less 10	ess_11	less 12	ess_13	less_14	less_15	less_16	ess_17	less_18	ess_19	ess_20	ess_21	ess_22
	T_MAX_mean_day_less	T_MAX_mean_day_	T_MAX_mean_day_less_3	T_MAX_mean_day_less	[_MAX_mean_day_less_5	MAX_mean_day_less	[_MAX_mean_day_less	_MAX_mean_day_less	MAX_mean_day_less	MAX_mean_day_le	MAX_mean_day_less	an_day_k	[_MAX_mean_day_less	MAX_mean_day_le	an_day_k	an_day_k		MAX_mean_day_le	MAX_mean_day_less	an_day_l	an_day_l.	an_day_k
	T_MAX_n	T_MAX_n	T_MAX_II	T_MAX_n	T_MAX_M	T_MAX_M	T_MAX_M	T_MAX_n	T_MAX_M	T_MAX_me	T_MAX_me	T MAX mean day	T_MAX_me	T_MAX_me	T_MAX_mean_day_	T_MAX_mean_day.	T_MAX_me	T_MAX_me	T_MAX_me	T_MAX_mean_day_less	T_MAX_mean_day_less	T_MAX_mean_day_less

## Methods Linear model

Four phenotypic data were analyzed:

- Milk yield (kg/hg)
- Somatic Cell Counts
- Protein content (%)
- Fat content (%)



 Phenotypic data = Parity + Days in Milk + Cow Age + EBV + Farm + Animal ID

 Fixed effects

 Random effects

- The residuals of the linear model were used to mitigate the effects of genetic factors or farm management
- They represent the data to be predicted for the artificial intelligence model

- The "**production**" dataset: dairy cows' records from 1990 to 2020 (AIA, ANAPRI)
- Pilot dataset: milk production from "Pezzata Rossa" in Friuli-Venezia-Giulia









## Methods Our pipeline



Figure 1. The process of supervised ML





Historical data

