

Utilizing Machine Learning and Mechanistic Understanding to Appreciate the Impact of pH, DO, and pCO₂ on Upstream AAV Yield and Product Quality

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SESSION: AAV critical quality attributes

DO: Dissolved Oxygen
pCO₂: Dissolved CO₂

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- I am a full-time employee at Solid Biosciences

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Why should you care about pH, DO, and pCO₂?

They tend to vary as you scale-up your bioreactor, impacting PQ!

Google Scholar: >250K publications on the impact of scale-up upon product quality. Established literature is mAb centric. Literature considering gene therapy is limited.



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Regular article

A systematic mass-transfer modeling approach for mammalian cell culture bioreactor scale-up

Chuan He^{a,b,d}, Pei Ye^b, Haibin Wang^c, Xiao Liu^b, Feng Li^{a,b} ✉

Bioprocess and Biosystems Engineering (2025) 48:1619–1635
<https://doi.org/10.1007/s00449-025-03182-w>

CRITICAL REVIEW



Scale-down bioreactors—comparative analysis of configurations

Prasika Arulrajah^{1,2} · Anni Elina Lievonon³ · Dilara Subaşı³ · Subhashree Pagal³ · Dirk Weuster-Botz¹ · Anna-Lena Heins²

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Bioprocess Biosyst Eng (2017) 40:251–263
DOI 10.1007/s00449-016-1693-7



RESEARCH PAPER

Investigation of the interactions of critical scale-up parameters (pH, pO₂ and pCO₂) on CHO batch performance and critical quality attributes

Matthias Brunner^{1,2} · Jens Fricke^{1,2} · Paul Kroll^{1,2} · Christoph Herwig^{1,2}

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BIOTECHNOLOGY
and
BIOENGINEERING

Characterization of hybridoma cell responses to elevated pCO₂ and osmolality: Intracellular pH, cell size, apoptosis, and metabolism

Vivian M. deZengotita, Albert E. Schmeizer, William M. Miller ✉

First published: 04 January 2002 | <https://doi.org/10.1002/bit.10176> | [VIEW METRICS](#)



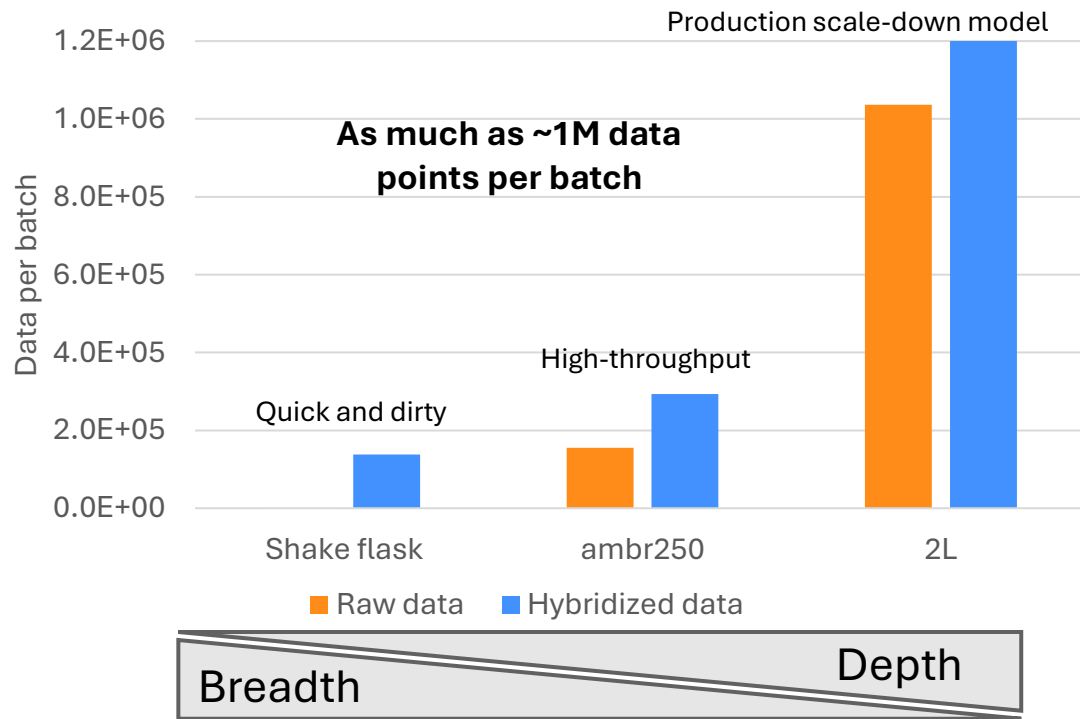
So pH, DO, pCO₂ matter...what to do about it?

We executed 24 related batches with goal to:

- Evaluate process sensitivity by directly or indirectly manipulating pH, pCO₂, or DO profile.
- Determine impact to batch performance at harvest via 3 assays.
 - ddPCR yield
 - Multiplex ddPCR: Genomic Integrity
 - 2 primers used simultaneously to verify that the genome is complete
 - Full Capsid Ratio: ddPCR/Capsid ELISA
 - High-throughput method that overestimates on an absolute basis, but predictive on relative basis

Why is Process Development uniquely poised to leverage ML?

Our experiments are rich with data! Below are the 3 small-scale platforms we use with relative advantages and disadvantages.



Product quality predictions are complex. What can machine learning offer?

Predictive Modelling

- Predict outputs such as GOI ddPCR titer, full ratio (GOI ddPCR/Capsid ELISA), and multiplex ddPCR genomic integrity
- Enable “what if” questions to be answered without the need for added experiments.



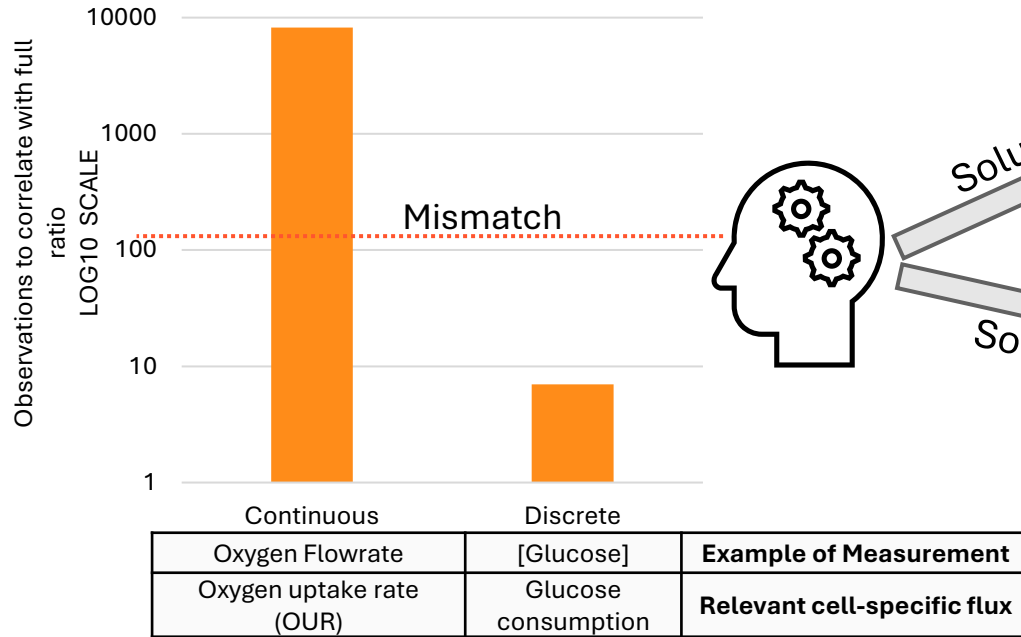
If you do predictive modeling, don't waste this opportunity to assess batch normalcy (using same dataset)!

Batch Normalcy Detection

- Determine normal batch to batch variability
- Determine whether or not a given batch is performing normally

Why is it a challenge to apply ML to process development? What shortcomings are common when applied?

The challenge: Sample Frequency divergence



Common shortcomings:

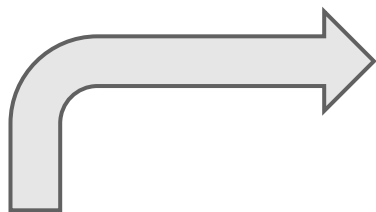
Predict outcome with separate models (even though data sets inherently related)

Predict outcome with unbalanced model with ~1000x the continuous data for a given variable as compared to discrete

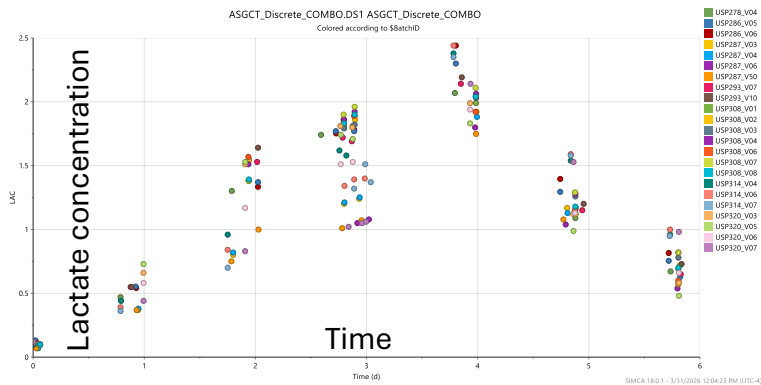
Note: Each observation is an individual recorded data point provided to the model.

Solution: Hybridize your datasets using metabolic flux analysis

Leverage entire data set, not a subset

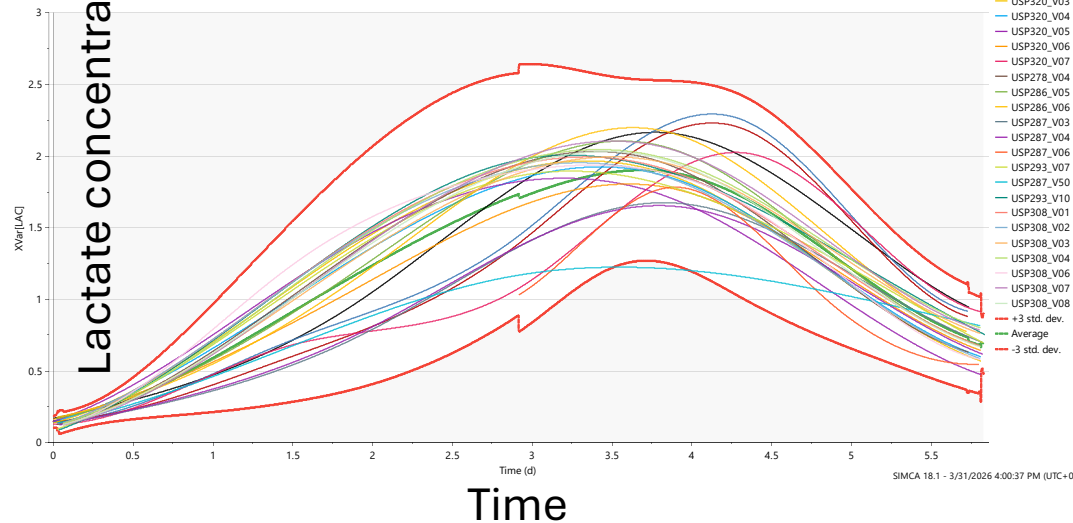


Discrete



Continuous

LAC - (M2, OPLS), All Batches PI Spline
ASGCT_Combo_Spline_30Mar2026



Multivariate predictions by 3 ML models

Level playing field: Same dataset for all models. 24 batches x 180K variables.

1) Hybridized dataset (discrete->continuous)

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
pCO ₂	pO ₂	Viable Cell Density (VCD)	Viability	Glutamax	ASN	ASP	GLC	GLU	K	LAC	LDH	Na	NH ₃	Pyruvate	Osmolality

2) Online dataset (continuous by nature)

17	18	19	20	21	22
DO	pH	Temperature	CO ₂ Flow Rate	Base Flowrate	O ₂ Flowrate

3) Batch performance

23	24	25
ddPCR titer	Capsid Full Ratio	Genomic Integrity

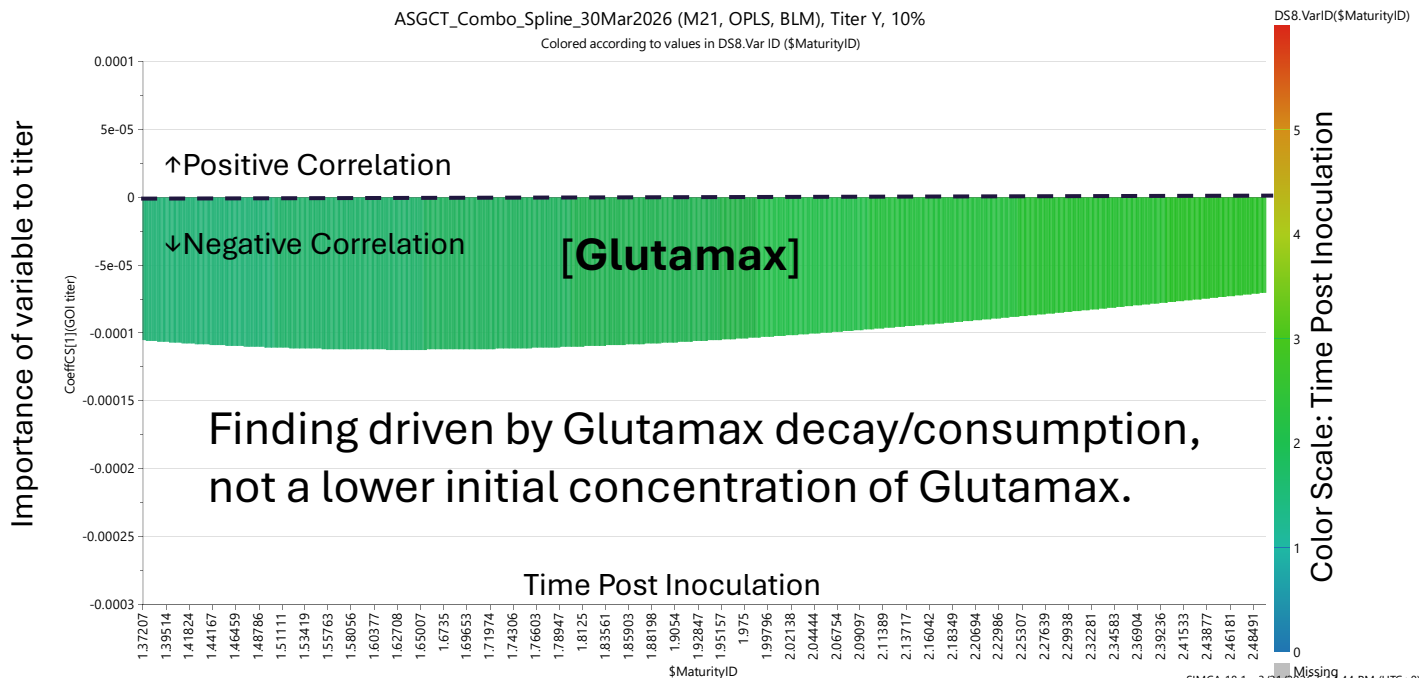
24 batches insufficient



ML Model	Orthogonal Partial Least Squares (OPLS)	Random Forest (RF)	Bayesian Neural Networks (BNN)
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Out of ~180K variables, what are the top 1% of ddPCR harvest titer correlates? When do they matter?

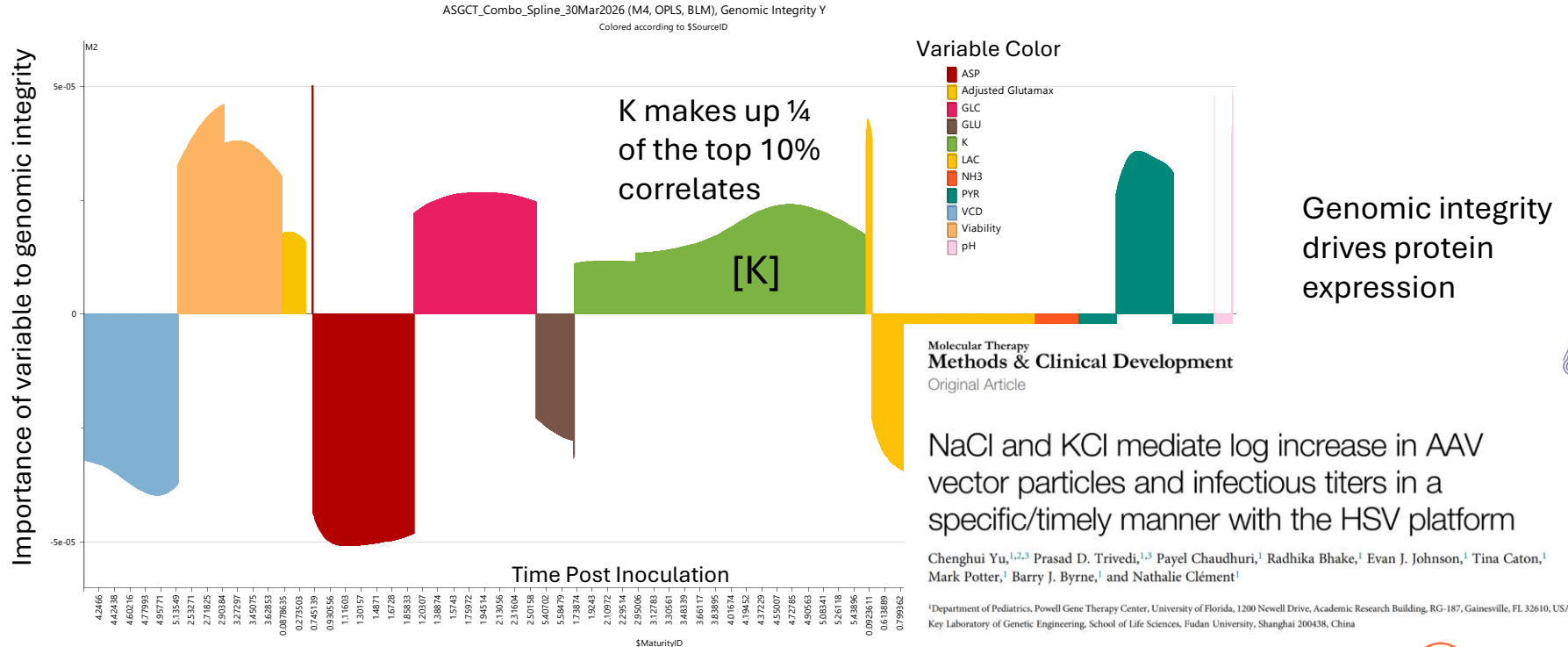
- [Glutamax] most relevant in 36 hours prior to Transfection. Lower the glutamax, higher the titer.
- Second most significant in Random Forest (RF), most significant in Orthogonal Partial Least Squares (OPLS).



Note:
Glutamax is a dimer of Gln and Ala

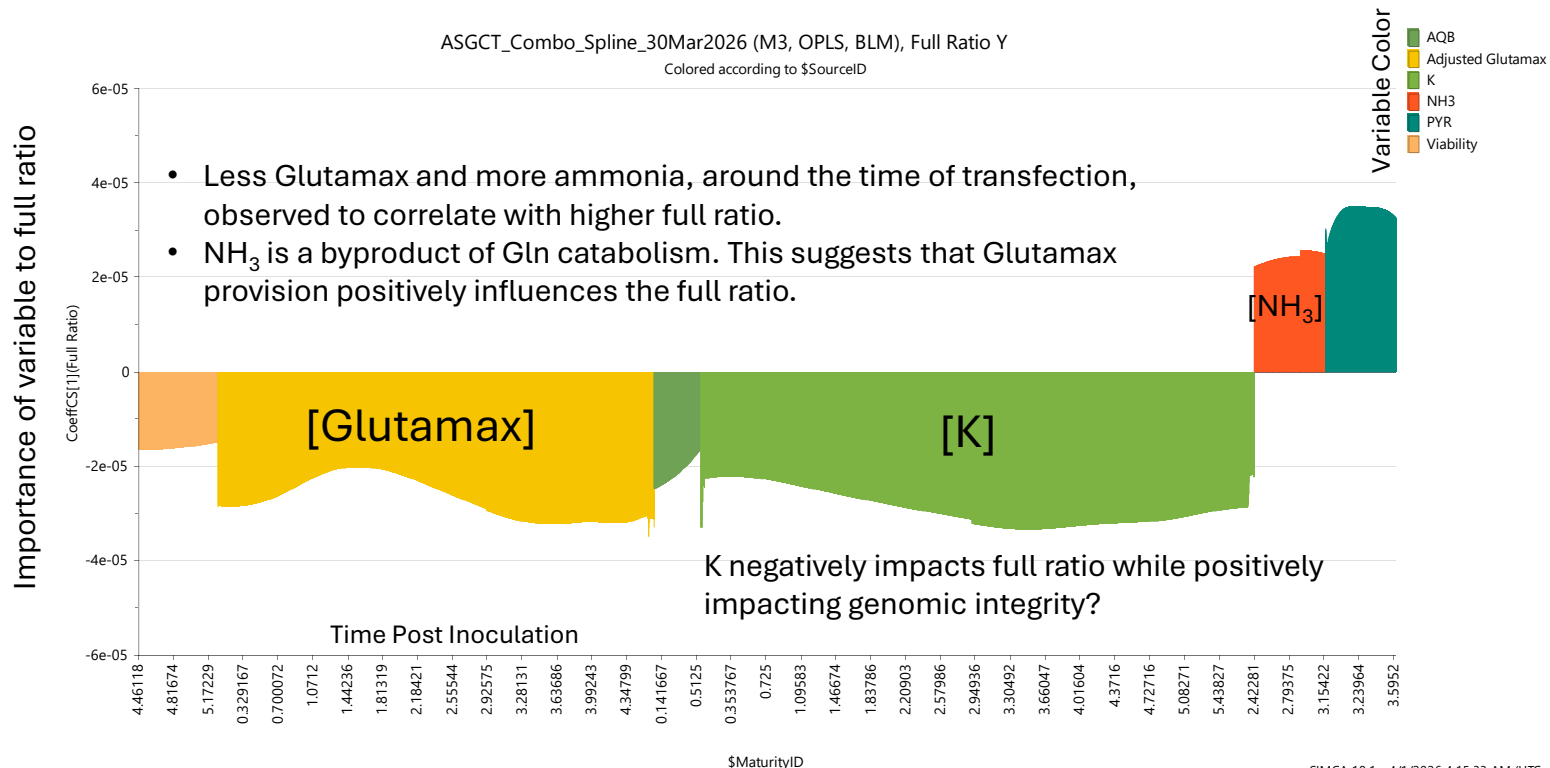
What are the top 10% of genomic integrity correlates? When do they matter?

[Potassium] ([K]) was a significant factor in all 3 ML models. [K] correlated with genomic integrity most strongly 1-2 days post transfection (period of peak ddPCR productivity). Higher [K], higher genomic integrity.



What are the top 10% of capsid full ratio correlates? When do they matter?

When examining top 10% of correlates in Orthogonal Partial Least Squares, Glutamax and Potassium (K) make up 70% of it. Lower [K] or [Glutamax], higher capsid full ratio. Likewise, Random Forest highlighted the importance of these variables.



Conclusions and recommendations for applying ML

- When applying ML, context matters! pH, DO, pCO₂ might not correlate with PQ directly, but they directly drove downstream metabolism which did correlate!
- We applied 3 ML approaches in parallel. Corroborative data is invaluable and tangible with ML.
- ML offers correlations, not causations. Logical deduction and systematic understanding remain crucial to successfully leveraging ML.
- Higher glutamax decay/consumption positively corresponded with yield and full ratio. Conversely, higher ammonia did not negatively correlate with yield or full ratio. At some point, ammonia will become toxic, but that limit was not observed at 2-3mM. Additional glutamax provision has the potential to improve full ratio and titer and merits future exploration.
- Potassium positively correlated with genomic integrity but negatively correlated with full ratio? Within similar window of time? Corroborative assessment needed (e.g. AUC) given that ddPCR to Capsid ELISA tends to overestimate full ratios. If conflict can be addressed, given the reported correlation of genomic integrity to potency within literature, and observed correlation of potassium to genomic integrity, future exploration is merited.

Thank you!

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