Integrating Machine Learning with Mathematical Modelling for Precision Aquaculture

Kheng Pak Kevin Wo*, Hong Yu, Say Chye Joachim Loo

School of Materials Science and Engineering, Nanyang Technological University, 50 Nanyang Avenue, Singapore 639798

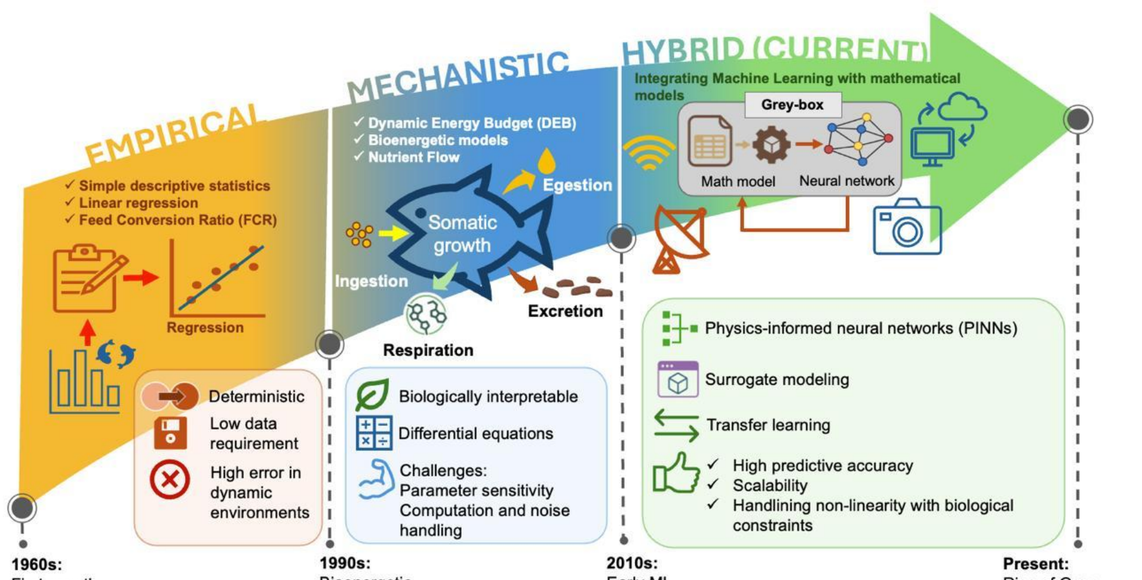
Introduction

- Global aquaculture production is growing rapidly, necessitating precise feeding optimization, biomass estimation and environmental management.
- Traditional aquaculture management relies on farmer's experience, failing to account for dynamic biological responses.
- The integration of machine learning (ML) can help achieve precision aquaculture by simulating real-time farm conditions and forecasting fish growth and health.

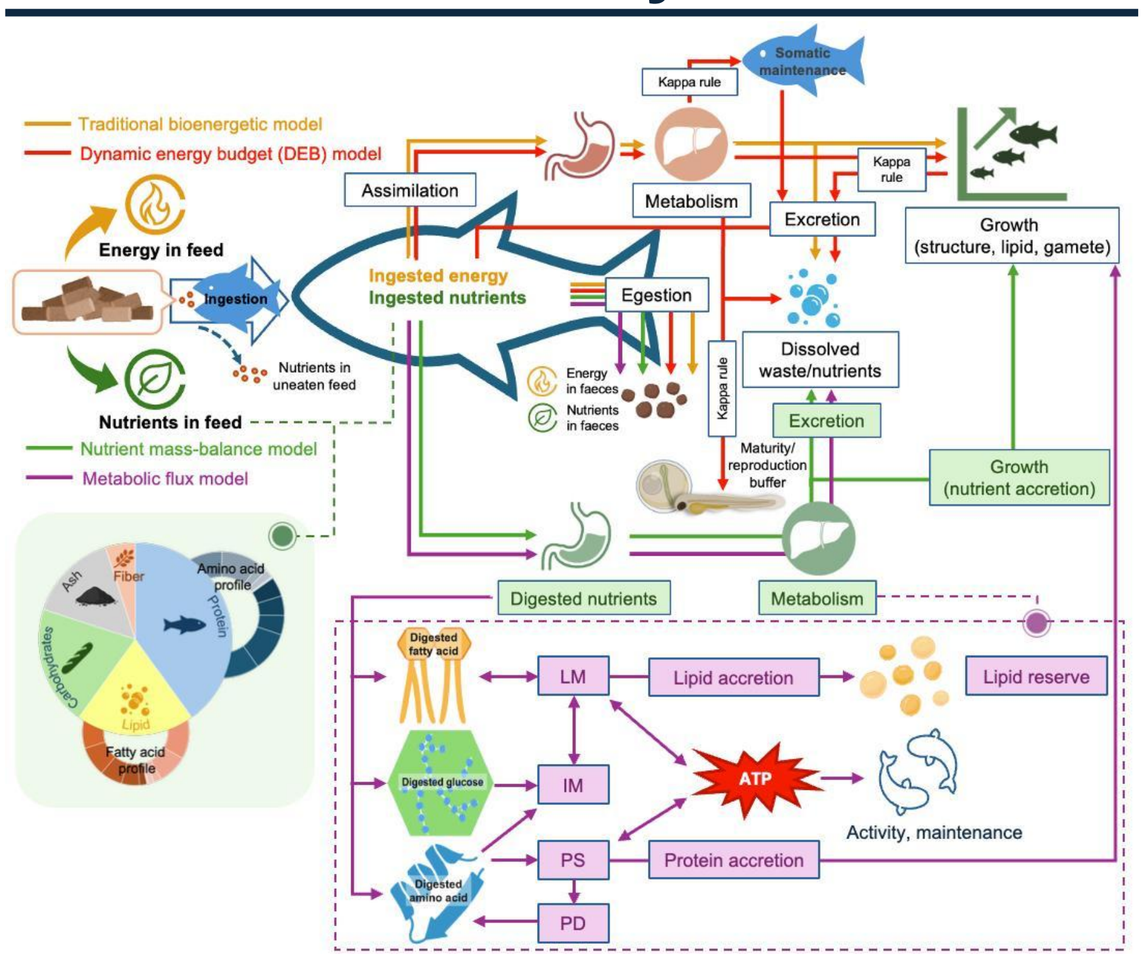
Objective

1. To evaluate the strengths and limitations of mathematical versus ML models in aquaculture.
2. To map out frameworks where hybrid "Grey-Box" modeling successfully integrates biological constraints with machine learning, including surrogate models, data-driven variable estimation and. physics-informed neural networks (PINNs).
3. To explore how multi-modal sensor fusion and reinforcement learning (RL) can build closed-loop digital twins for autonomous, real-life farm management.

1. Evolution of Modelling Landscape



2. Mathematical Modelling of Nutrient Pathways



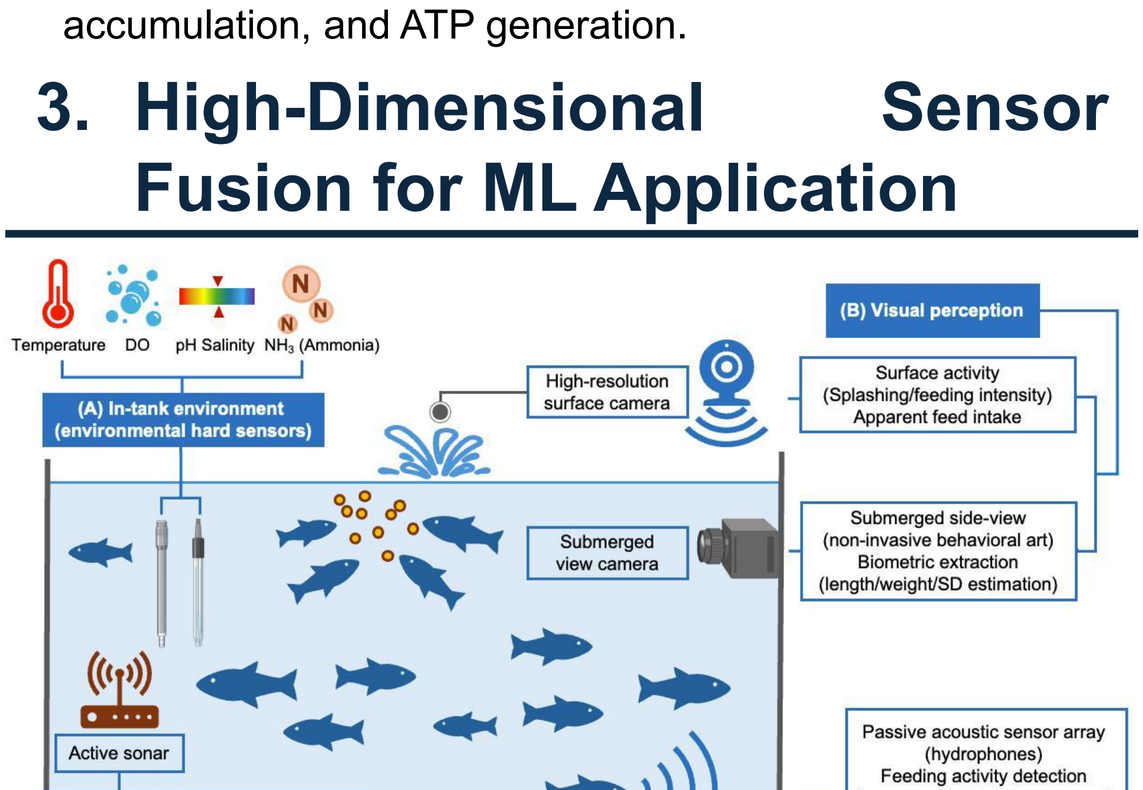
- **Traditional bioenergetics**: based on energy balance

$$C = G + R + F + U$$

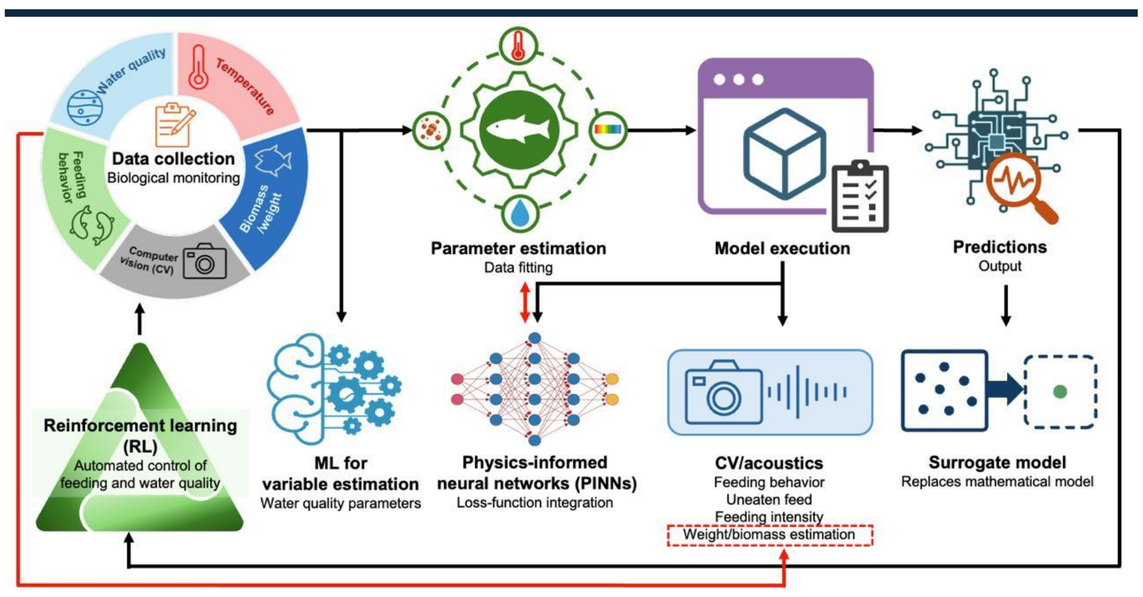
where energy from consumption (C) is partitioned into growth (G), respiration (R), feces (F), and excretion (U).

- **Dynamic energy budget (DEB)**: employs differential equations to route energy through a reserve compartment governed by a fixed kappa rule.
- **Nutrient flux**: tracks processing of proteins, lipids, and carbohydrates to model muscle composition, lipid accumulation, and ATP generation.

3. High-Dimensional Sensor Fusion for ML Application

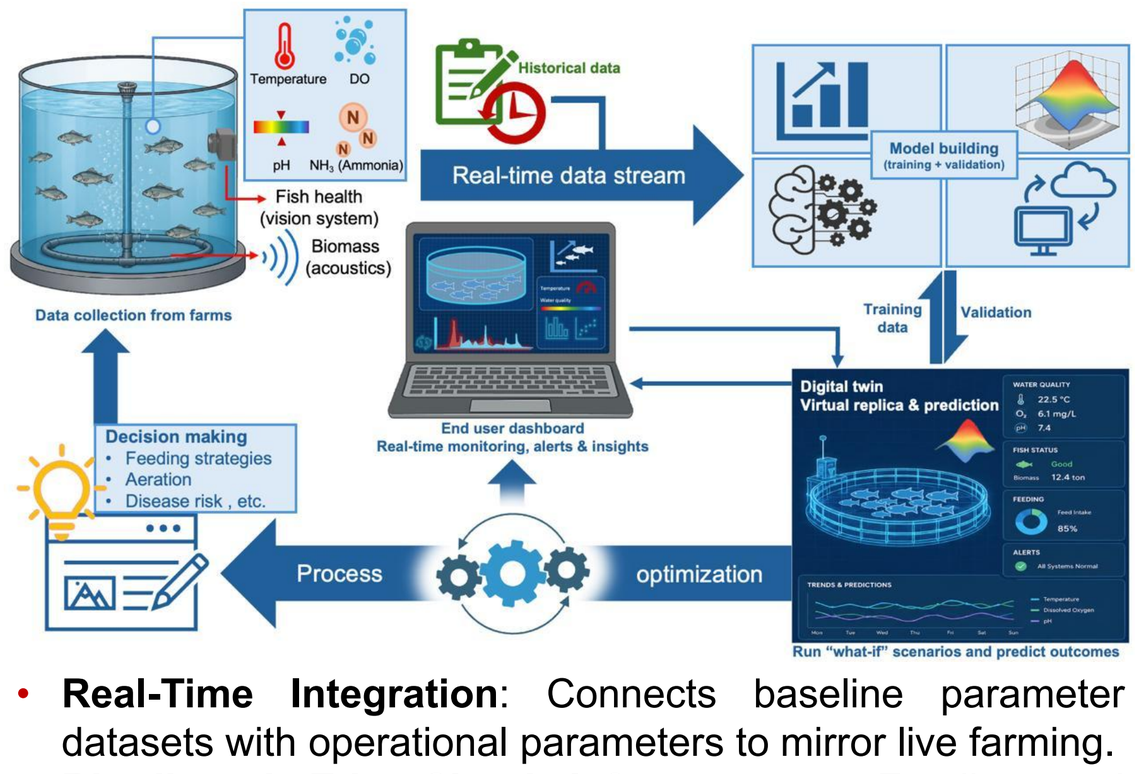


4. Hybrid "Grey-Box" Model Framework



- **Surrogate Modelling**: Bayesian optimization to approximate complex bioenergetic equations from simulation data, reducing computation time.
- **DL for Spatiotemporal Water Quality Prediction**: Recurrent networks and spatial interpolation forecast and map dynamic variables like NH_3 and DO.
- **Physics-Informed Neural Networks (PINNs)**: Embeds mechanistic differential equations into loss functions.
- **Computer Vision and Acoustic Analysis**: Non-invasive biomass estimation and fish behavior quantification from underwater images and sound spectrograms for fine-tuning of model predictions.
- **Reinforcement Learning**: Automates closed-loop control via agents that optimize feeding rates and water quality.

5. Digital Twin Ecosystem for Precision Aquaculture



- **Real-Time Integration**: Connects baseline parameter datasets with operational parameters to mirror live farming.
- **Distributed Edge-Cloud Infrastructure**: Feeding and aerator valves are controlled at the local edge layer, while large-scale models are processed at the global cloud layer.
- **What-If Optimization**: Allows farmers to evaluate predicted production outcomes across complex environmental conditions like heatwaves or hypoxia.

6. Conclusion

- Transitioning to a hybrid framework allows for biologically-grounded, real-time forecasting in precision aquaculture.
- Incorporating high-dimensional perception layers with closed-loop controllers to mathematical modelling creates a scalable framework toward high-fidelity digital twins.

References:

1. Dumas et al. *Aquac. Res.* **2010**, *41*, 161.
2. Kooijman. *Dynamic Energy Budget Theory for Metabolic Organisation*, **2009**.
3. Vo et al. *Electronics* **2021**, *10*, 2882.
4. Li & Du. *Artif. Intell. Rev.* **2022**, *55*, 4077.