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An Artificial Intelligence Model for Bathing Water Quality Early Warning Systems

M.Y. Lam and R. Ahmadian

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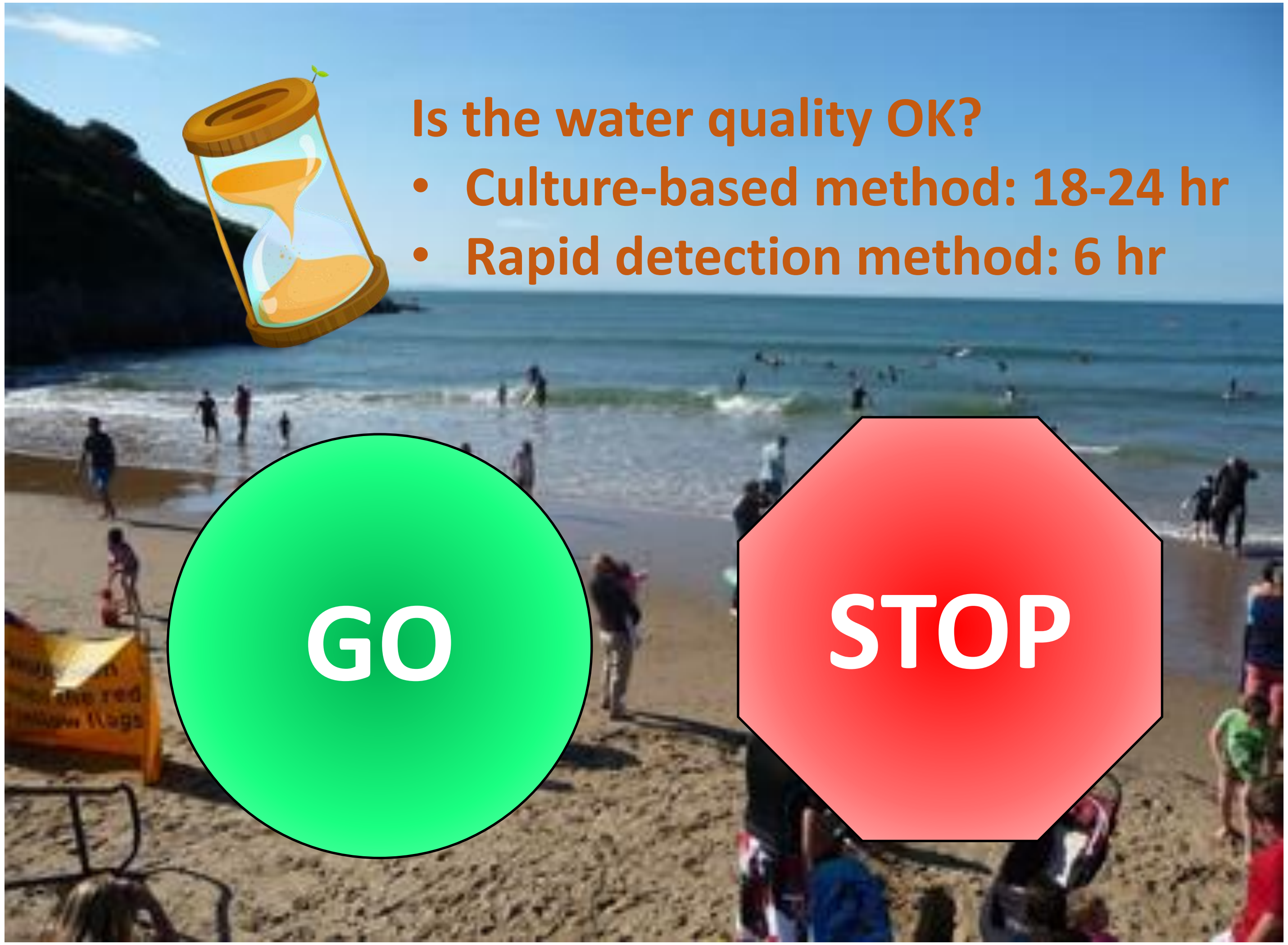
Cardiff University Prifysgol Caerdydd | eeres4water | European Union European Regional Development Fund | 1872 Prifysgol Aberystwyth University | smart coasts

Outline

- Need for real-time predictive models for bathing water quality early warning systems
- A novel Gamma-GA-ANN data-driven model
- Model testing at Swansea Bay, UK for predicting *Enterococci* and *E Coli*
- Conclusion

Public warning systems for bathing water quality

- Pathogen in bathing water cause public health problems
- Warning systems to inform the public about poor water quality
- Real-time prediction methods required
- This presentation introduces a novel predictive method



https://www.tourismforall.co.uk/news/read/2019/07/swansea-beach-adds-more-accessible-facilities-b77

Water quality prediction models

- Benefit aquaculture and water treatment
  - Evaluate environmental management strategies
  - Reduce energy use in water treatment: treat wastewater only to the required levels but not cleaner

Wastewater Treatment
Works (WWTW)

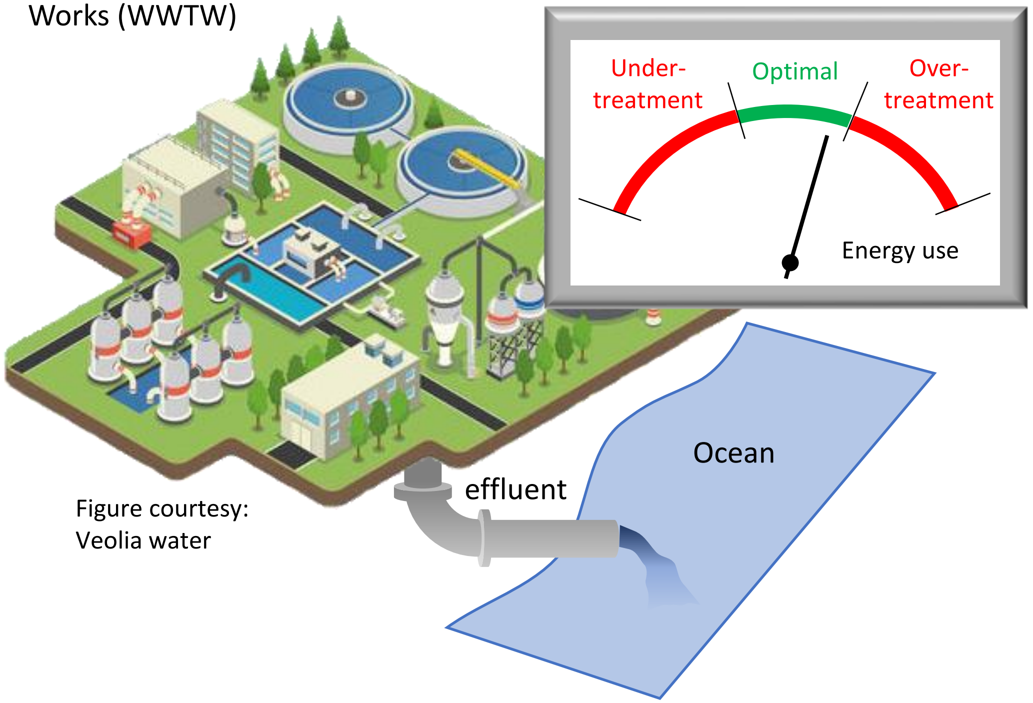
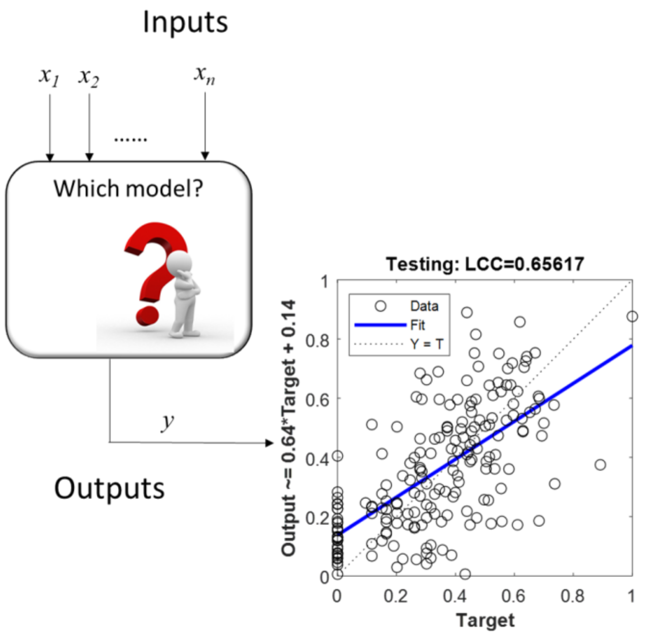


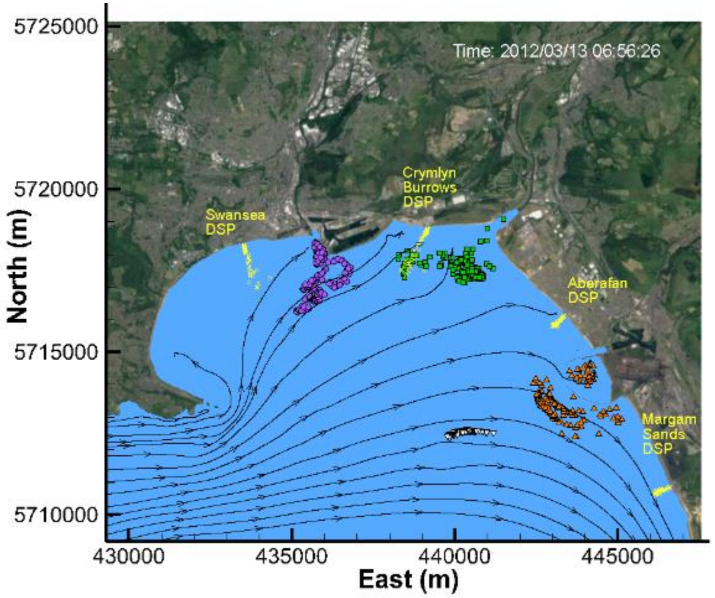
Figure courtesy:
Veolia water

Types of water quality models

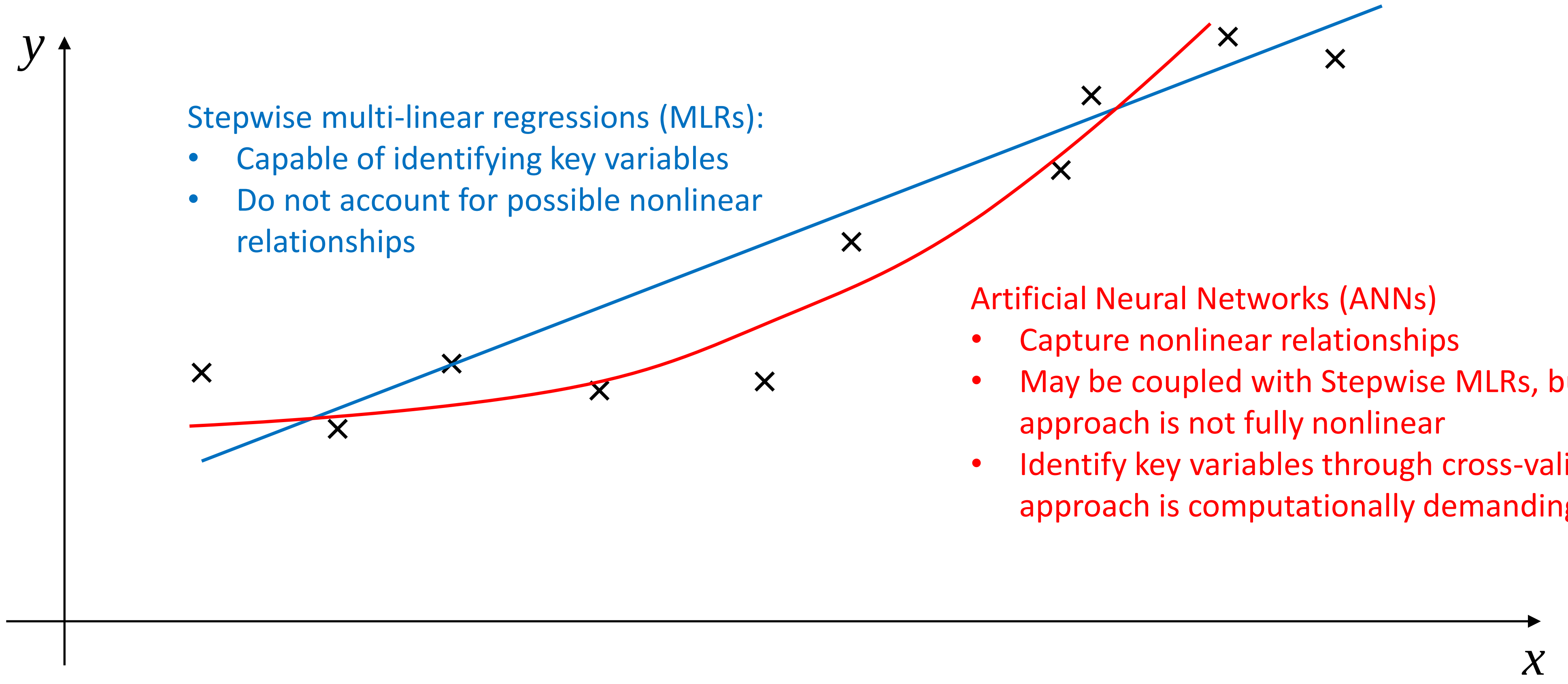
- Artificial Intelligence (AI) models
  - Establish relationship between explanatory variables and bacteria concentrations from measured data
  - Require less computational power – timely prediction



- Hydro-environmental models
  - Solve the flow and bacterial equations
  - Require (i) detail site knowledge, and (ii) high computational power
  - Provide understanding transport and fate of FIO



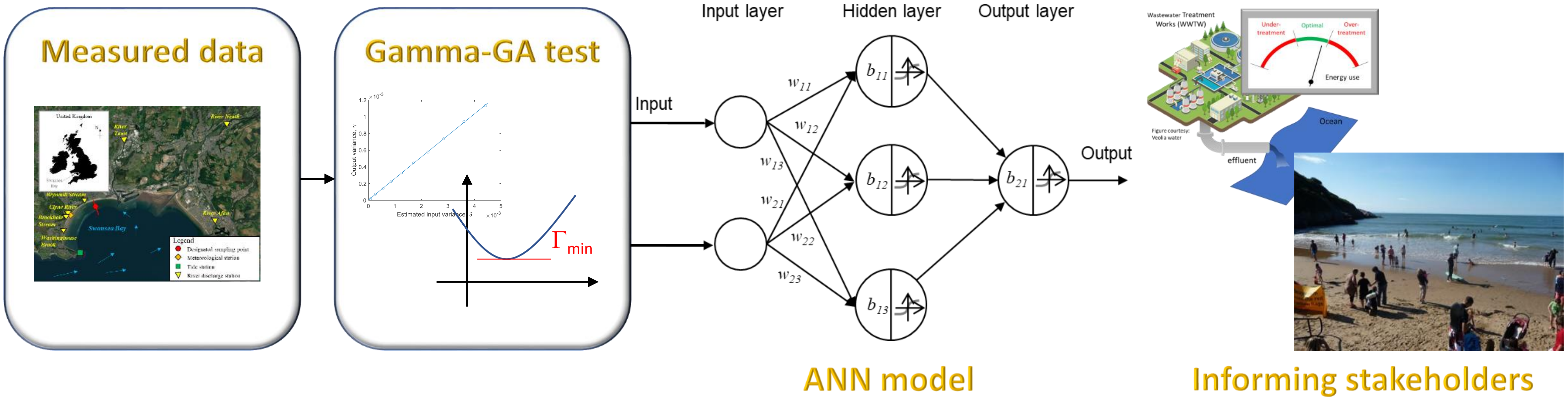
Linear and nonlinear data driven models



- Propose a Gamma test-Genetic Algorithm-ANN (Gamma-GA-ANN) model for full nonlinear variable identification and water quality prediction

Gamma-GA-ANN model

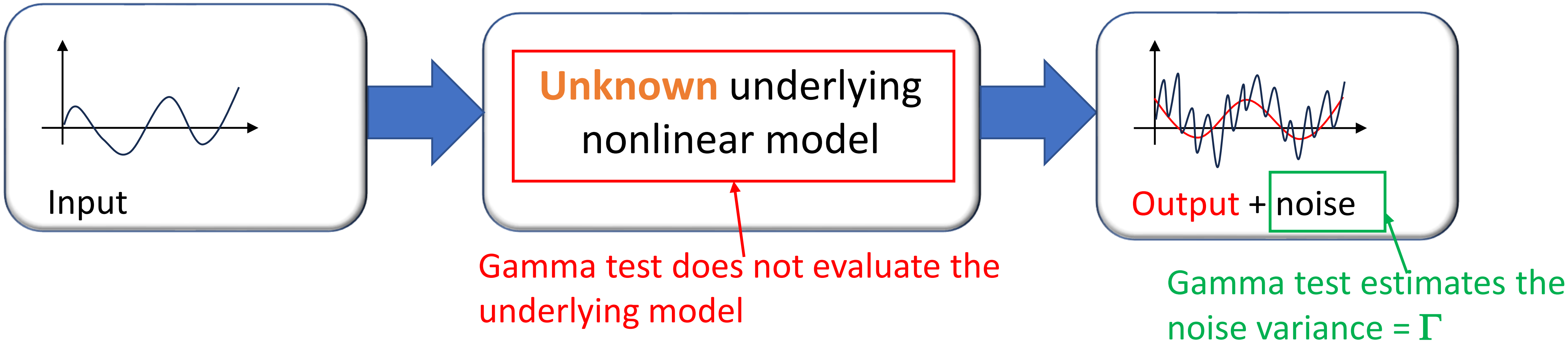
- Method outline:
  - Obtain data with sensors from the site
  - Apply Gamma-GA tests to identify key variables governing FIO concentrations
  - Predict FIO concentrations by ANN models
  - Inform water treatment operators and swimmers of impending poor water quality



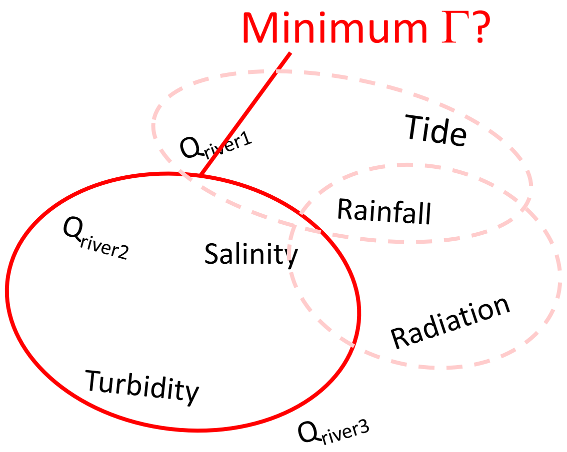
European Union
European Regional Development Fund

Gamma - GA test

FIO concentration in coastal water: An input-system-output representation

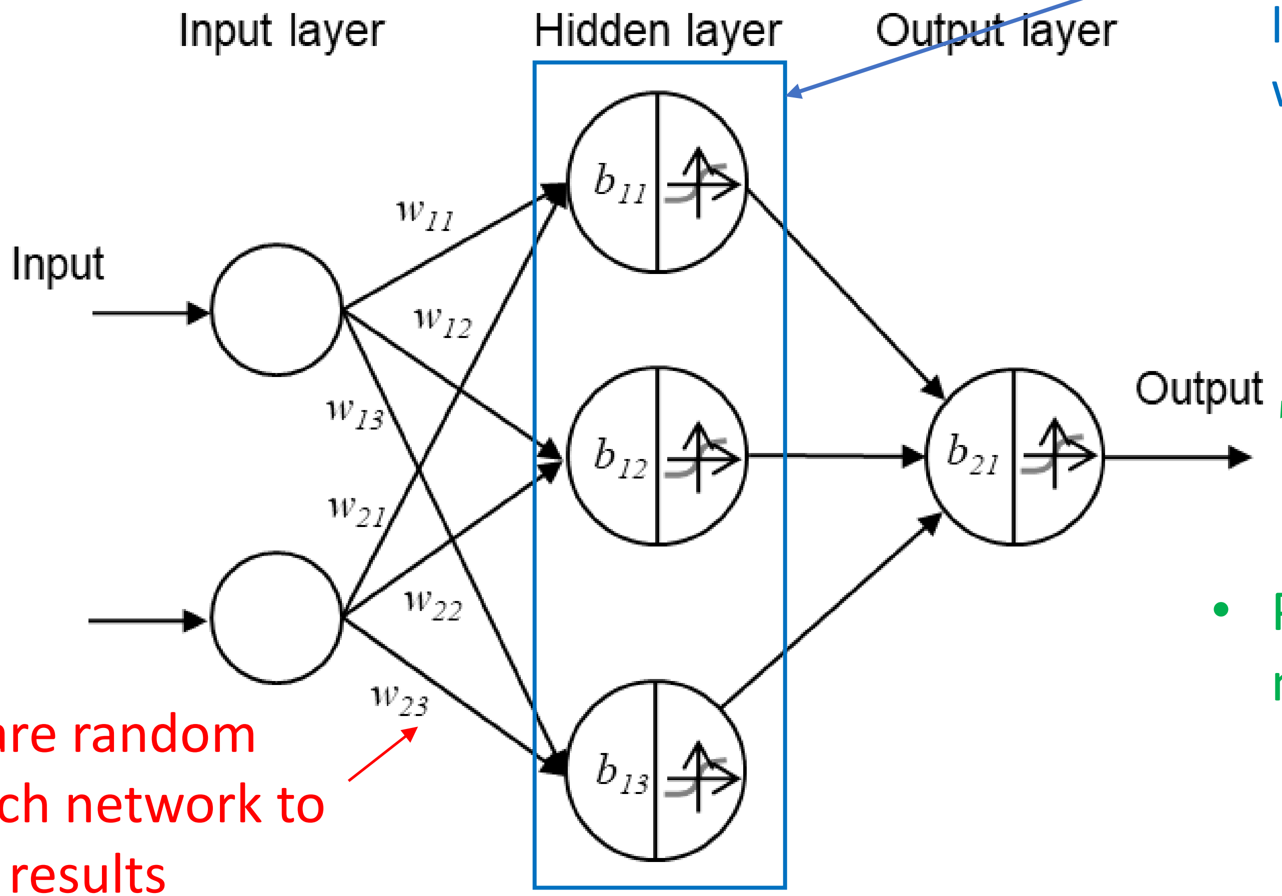


- Variable identification: Gamma-GA test
  - The key variables are the variables that give the smallest Γ.
  - Conduct Gamma tests to all possible variable combinations → computationally demanding.
  - Genetic Algorithm (GA) is employed



Artificial Neural Network

- Feed forward network



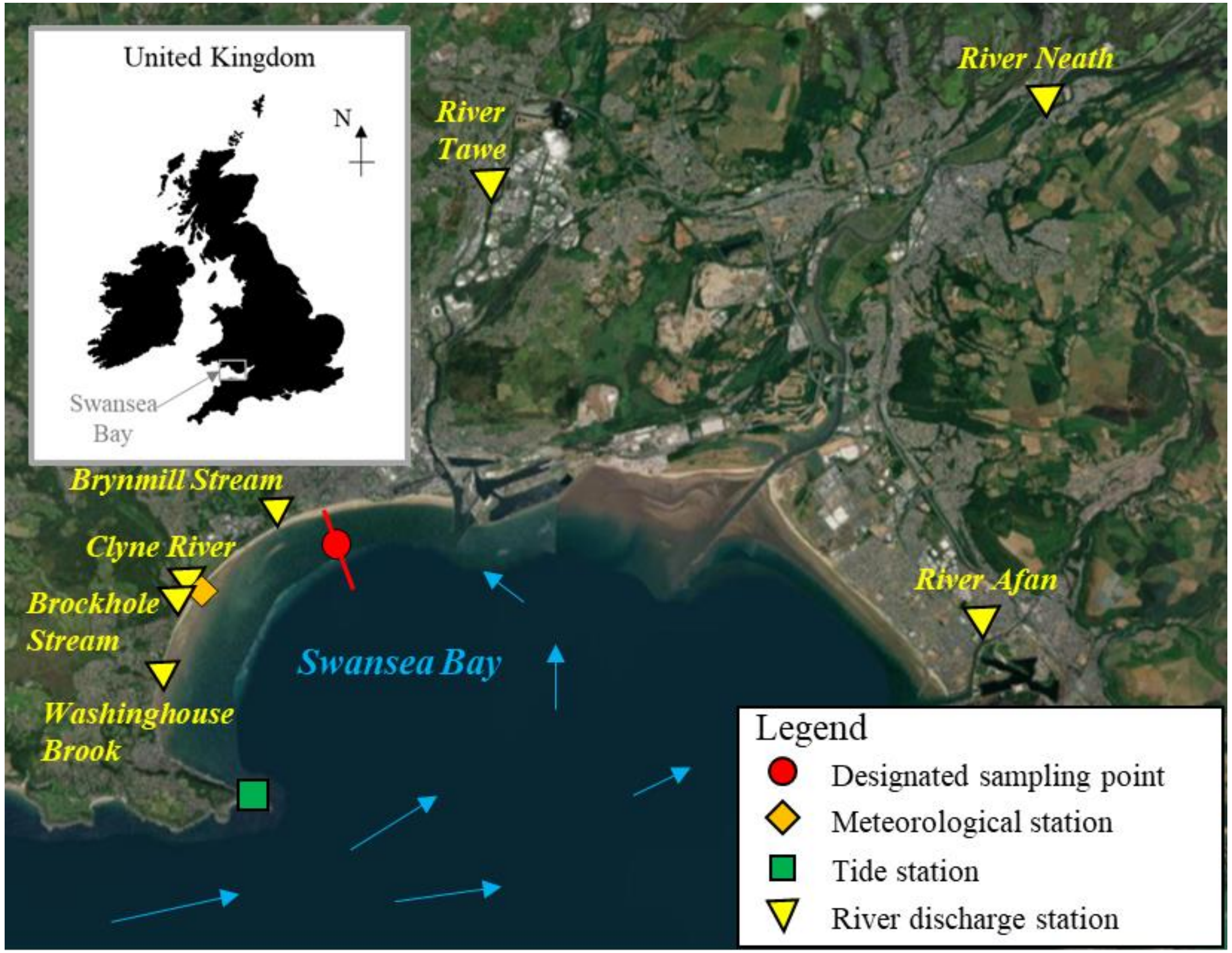
- One hidden layer was sufficient in our study
- Increased the number of hidden layer nodes stepwise and stop when overfitting occurs

- Performance function: mean square error (MSE)

- Initial weights are random
- 300 runs for each network to ensure optimal results

Field data from Swansea Bay, UK

- Popular beaches such as Swansea Beach
- Sampling period: bathing season of 2011
- FIO Sampling interval: 30 min
- Total number of data:
  - 204 variables (including time-lagged data) x 949 time instants = 193596 data
- Remove redundant variables with collinearity test:
  - 23 variables were retained

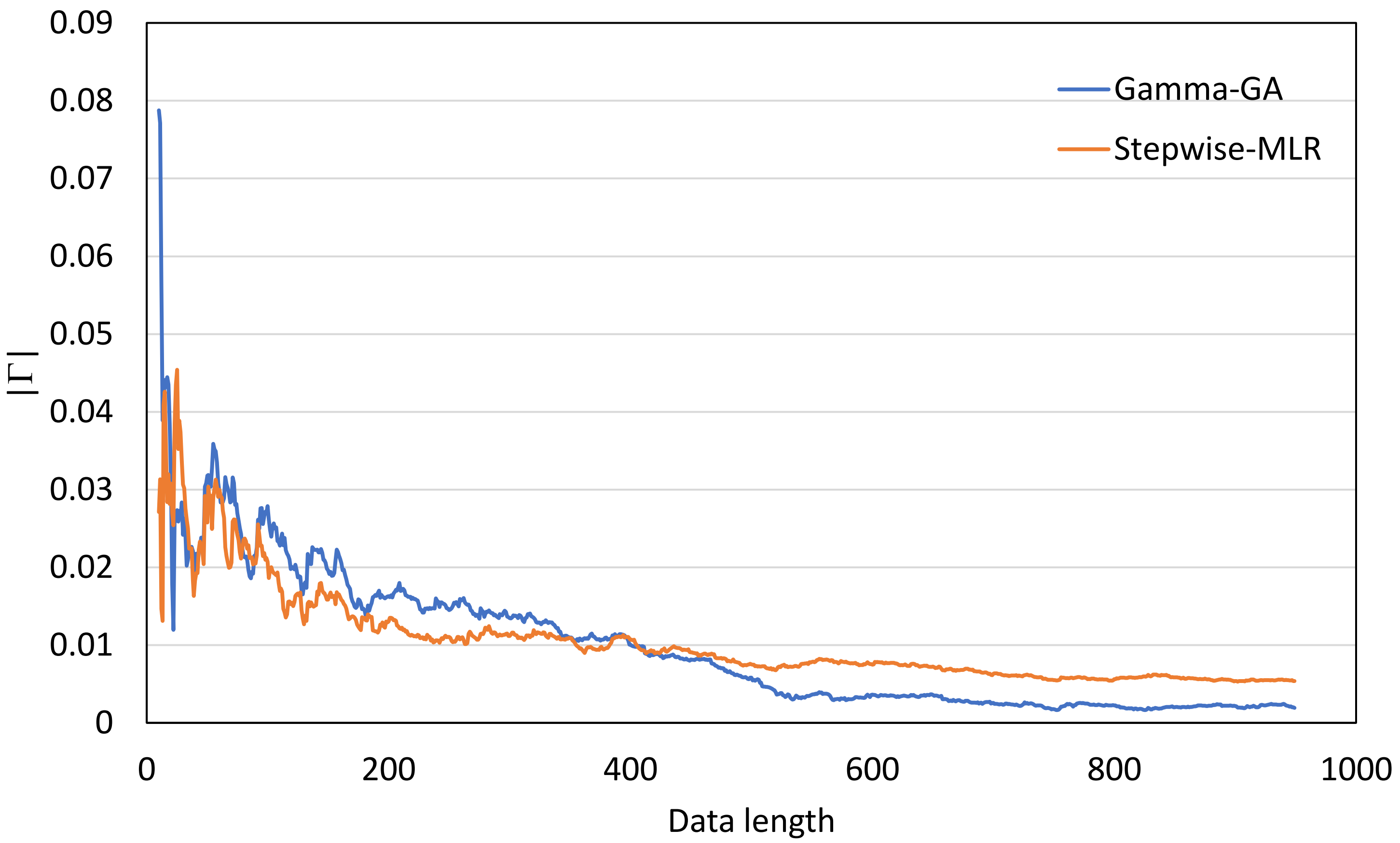


Variables selected by Gamma-GA test

- Tide level and Wind were always selected
    - Consistent with previous mechanistic and AI model results.
- Streamflow was included by the Gamma-GA test for *Enterococci* only
    - River flows are known to be important FIO sources, but
    - Flow rate alone does not fully characterize the effect of rivers

Variables identified from the correlation analysis	Enterococci		E Coli	
	Gamma test	Stepwise linear analysis	Gamma test	Stepwise linear analysis
Streamflow [lag 10 h]	1	0	0	1
Mumbles Level [lag 2 h]	0	0	0	0
Mumbles Level [lag 4 h]	1	0	1	1
Mumbles Level [lag 6 h]	1	1	1	0
Global Radiation [lag 2 h]	0	1	0	1
Global Radiation [lag 4 h]	0	0	1	0
Global Radiation [lag 6 h]	1	0	0	0
Temperature [lag 2 h]	1	0	0	1
Temperature [lag 6 h]	1	0	1	0
Relative Humidity [lag 2 h]	0	1	0	1
Relative Humidity [lag 8 h]	1	0	1	0
Cum. of Rain [lag 2 h]	0	0	0	0
Cum. of Rain [lag 3 h]	0	0	0	0
Cum. of Rain [lag 4 h]	0	0	0	0
Cum. of Rain [lag 6 h]	0	0	0	0
Cum. of Rain [lag 8 h]	0	0	0	0
Cum. of Rain [lag 10 h]	0	0	0	0
Cum. of Rain [lag 12 h]	0	1	0	0
Wind Speed N [lag 2 h]	0	1	1	1
Wind Speed N [lag 6 h]	0	0	1	0
Wind Speed N [lag 10 h]	0	1	0	1
Wind Speed E [lag 2 h]	1	1	1	1
Wind Speed E [lag 10 h]	0	1	0	0

M-test



- Determine the necessary data length for successful AI model development
  - Gamma-GA test selected variables achieved better |Γ| when data length exceeds 500.
- The data were divided into training, validation and testing sets. The training set had more than 500 data points.

Model Comparison

		Key variable identification	
		Gamma-GA test	Stepwise linear (SL) regression
Prediction model	ANN	GG-ANN model	SL-ANN model
	SL	GG-Linear model	SL-Linear model

- Models that use ANN gave a superior predictive performance compared to linear regression models
- Gamma-GA-ANN model gave better prediction results for *Enterococci*

Enterococci

Realization 1						
	MSE			R^2		
	Training	Validation	Testing	Training	Validation	Testing
GG-ANN	0.0074	0.0157	0.0214	0.8369	0.6654	0.5361
SL-ANN	0.0210	0.0232	0.0260	0.5400	0.5079	0.4357
GG-Linear	0.0357		0.0399	0.2224		0.1348
SL-Linear	0.0311		0.0328	0.3235		0.2883
Realization 2						
	MSE			R^2		
	Training	Validation	Testing	Training	Validation	Testing
GG-ANN	0.0134	0.0172	0.0227	0.7177	0.6025	0.4993
SL-ANN	0.0257	0.0194	0.0295	0.4542	0.5518	0.3611
GG-Linear	0.0368		0.0352	0.2021		0.2246
SL-Linear	0.0312		0.0322	0.3229		0.2895
Realization 3						
	MSE			R^2		
	Training	Validation	Testing	Training	Validation	Testing
GG-ANN	0.0071	0.0188	0.0199	0.8292	0.6457	0.6156
SL-ANN	0.0192	0.0243	0.0225	0.5385	0.5418	0.5699
GG-Linear	0.0359		0.0393	0.1944		0.2403
SL-Linear	0.0320		0.0293	0.2812		0.4337

Model Comparison

- GG-ANN model did not always give better prediction for *E Coli* compared to SL-ANN
- Explanation:
  - This *Enterococci* data has more extreme values (17.8% of the data) compared to the *E Coli* data (8.9% of the data); and
  - GG-ANN model is better for capturing extreme values

E Coli

	MSE			R^2		
Realization 1						
	Training	Validation	Testing	Training	Validation	Testing
GG-ANN	0.0067	0.0159	0.0214	0.8396	0.6077	0.5312
SL-ANN	0.0096	0.0154	0.0174	0.7705	0.6198	0.6177
GG-Linear	0.0325		0.0342	0.2166		0.2482
SL-Linear	0.0297		0.0305	0.2838		0.3290
Realization 2						
	Training	Validation	Testing	Training	Validation	Testing
GG-ANN	0.0119	0.0178	0.0205	0.7208	0.5939	0.4801
SL-ANN	0.0113	0.0135	0.0188	0.7370	0.6914	0.5221
GG-Linear	0.0331		0.0315	0.2294		0.1996
SL-Linear	0.0299		0.0295	0.3041		0.2484
Realization 3						
	Training	Validation	Testing	Training	Validation	Testing
GG-ANN	0.0073	0.0146	0.0196	0.8066	0.6747	0.6337
SL-ANN	0.0091	0.0155	0.0186	0.7582	0.6539	0.6501
GG-Linear	0.0321		0.0363	0.1873		0.3181
SL-Linear	0.0297		0.0310	0.2501		0.4167

Performance table under EU rBWD classification

Gamma-GA-ANN models

		Observed: Not poor	Observed: Poor	
Predicted	Not poor	146	11	93%
Predicted	Poor	14	18	56%
		91% **Specificity**	62% **Sensitivity**	87%

SL-ANN models

		Observed: Not poor	Observed: Poor	
Predicted	Not poor	155	22	88%
Predicted	Poor	5	7	58%
		97% **Specificity**	24% **Sensitivity**	86%

Enterococci, Realization 1, testing set

Gamma-GA-ANN models

		Observed: Not poor	Observed: Poor	
Predicted	Not poor	170	6	97%
Predicted	Poor	8	5	38%
		96% **Specificity**	45% **Sensitivity**	93%

SL-ANN models

		Observed: Not poor	Observed: Poor	
Predicted	Not poor	172	8	96%
Predicted	Poor	6	3	33%
		97% **Specificity**	27% **Sensitivity**	93%

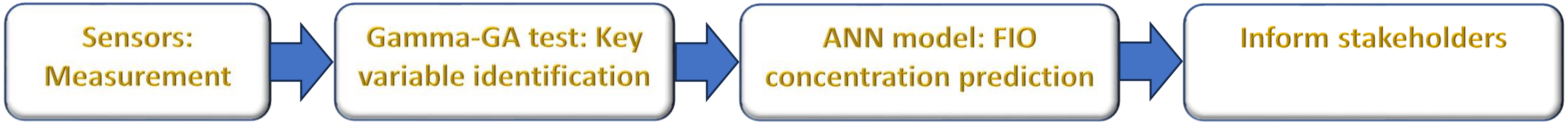
E Coli, Realization 3, testing set

- GG-ANN model improved the sensitivity for FIOs
  - Consistent with previous literature that nonlinear model captures better the extreme values

Specificity: % of NOT false alarm
Sensitivity: % of poor water quality identified
Overall accuracy: % of correct identification

Conclusion

- A data-driven GG-ANN model has been developed for FIO concentration prediction without unnecessary input variables



- GG-ANN model performance was evaluated at Swansea Bay, UK
  - Better predicted *Enterococci* for all three sets and most of the training sets for *E Coli*
  - Better in identifying events of poor water quality
  - Suitable for bathing water warning applications

https://www.tourismforall.co.uk/news/read/2019/07/swansea-beach-adds-more-accessible-facilities-b77

Thank you for listening

- Contact
  - M. Y. Arthur Lam: lamM7@cardiff.ac.uk
  - R. Ahmadian: AhmadianR@cardiff.ac.uk