

The Development of a Water Quality Forecasting System for Recreational Coastal Bathing Waters in Ireland

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Project Objectives

- European Bathing Water Directive requires the implementation of *early warning systems for bathing waters* which are subject to short-term pollution events.
- Coastal water quality prediction models and alert systems are being developed which aim to provide *short-term forecasts of bathing water*.
- These forecasts are based on the (modeled) relationship between fecal indicator bacteria and *multiple environmental variables*.



Key Project Components

- 1) Model Development & Testing: UCD Civil Engineering
- 2) Data & Model Infrastructure: UCD Computer Science
- **3) Water Quality Sampling:** UCD Microbiology & AgriFood and Biosciences Institute (AFBI)





Water Quality History Example @ Newcastle Beach



Environmental Variables from Previous Studies



Statistical Models for Bathing Water Prediction are *Data Hungry*

MÉRA Data



MÉRA Grid Points @ Newcastle Beach

- Many MÉRA grid points within a target catchment area
- Provides high spatial & temporal resolution (far exceeding what could be gathered by gauges)



MÉRA Grid Points @ Newcastle Beach

- Precipitation (& soil moisture) used from ALL points within the catchment area.
- Only the point closest to the sampling point is used for the other variables.



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Summary of Modelling Approaches

APPROACH	DESCRIPTION	STRENGTHS	WEAKNESSES		
Decision Threshold Optimizer	Determines what level of rainfall / streamflow has correlated with past FIB exceedance levels to predict future occurrences.	 Uses readily available data (e.g. rainfall, streamflow) Implemented in Excel 	 Low correlations between single variables & FIB levels Does not consider multiple-variable drivers. 		
Decision Tree Models	Trains models based on past relationship between environmental variables & FIB concentrations to predict future occurrences.	 Can utilize many variables Can represent non- linear responses. 	 Higher data requirements Can suffer from "over- training" 		
Ensemble Decision Tree Models	Generates probabilistic predictions of FIB concentrations, based on many individual Decision-Tree models.	 Less susceptible to "over-training" Improved predictive power 	 Driving variables are more difficult to interpret Higher data & technical requirements. 		

1. Model Development



1. Model Development



2. Model Implementation



2. Model Implementation

Predictions are for Saturday, August 31st 2019

Ballyholme@11:00 - General Status -	Ballywalter@11:00 - General Status -	<mark>Castlerock@11:00</mark> - General Status -	Clogherhead@11:00 - General Status -	Enniscrone@11:00 - General Status -	<mark>Ladysbay@11:00</mark> - General Status -	<u>Newcastle@11:0(</u> - General Status -	<u>Portrush@11:00</u> - General Status -	<mark>Waterfoot@11:00</mark> - General Status -
General_Class	General_Class	General_Class POOR Concent Disc	General_Class	General_Class	General_Class EXCELLENT	General_Class POOR Concert Dire	General_Class EXCELLENT	General_Class POOR
PASS	PASS	General_Bin FAIL	PASS	PASS	PASS	General_Bin	PASS	General_Bin FAIL
- IE Related -	- IE Related -	- IE Related -	- IE Related -	- IE Related -	- IE Related -	- IE Related -	- IE Related -	- IE Related -
IE_Log 1.539645765 IE_Value 34.645414806 IE_Class EXCELLENT	IE_Log 1.646271057 IE_Value 44.286469201 IE_Class EXCELLENT	IE_Log 1.340914536 IE_Value 21.923734614 IE_Class	IE_Log 1.094602186 IE_Value 12.433751583 IE_Class	IE_Log 1.138361069 IE_Value 13.751848164 IE_Class	IE_Log 1.620812357 IE_Value 41.764987575 IE_Class	IE_Log 2.964792230 IE_Value 922.130166980 IE_Class DOOR	IE_Log 1.281588040 IE_Value 19.124409742 IE_Class	IE_Log 2.522965162 IE_Value 333.399667168 IE_Class POOR
IE_Bin PASS	IE_Bin PASS	IE_Bin PASS	IE_Bin PASS	IE_Bin PASS	IE_Bin PASS	IE_Bin FAIL	IE_Bin PASS	IE_Bin FAIL
- EC Related -	- EC Related -	- EC Related -	- EC Related -	- EC Related -	- EC Related -	- EC Related -	- EC Related -	- EC Related -
EC_Log 1.654335810 EC_Value 45.116542439 EC_Class <u>EXCELLENT</u> EC_Bin PASS	EC_Log 1.582200637 EC_Value 38.212076337 EC_Class <u>EXCELLENT</u> EC_Bin PASS	EC_Log 3.219891747 EC_Value 1659.173286564 EC_Class POOR EC_Bin FAIL	EC_Log 1.097259954 EC_Value 12.510076158 EC_Class EXCELLENT EC_Bin PASS	EC_Log 2.381682193 EC_Value 240.814255636 EC_Class <u>EXCELLENT</u> EC_Bin PASS	EC_Log 1.543026367 EC_Value 34.916151305 EC_Class <u>EXCELLENT</u> EC_Bin PASS	EC_Log 3.611563517 EC_Value 4088.495428671 EC_Class POOR EC_Bin FAIL	EC_Log 1.776059005 EC_Value 59.711640707 EC_Class <u>EXCELLENT</u> EC_Bin PASS	EC_Log 2.311484358 EC_Value 204.872826124 EC_Class <u>EXCELLENT</u> EC_Bin PASS
end of 11:00:00	end of 11:00:00	end of 11:00:00	end of 11:00:00	end of 11:00:00	end of 11:00:00	end of 11:00:00	end of 11:00:00	end of 11:00:00

Bathing Water Quality Forecasts utilizing HARMONIE Data

2. Model Implementation: Public Notification

Website

Ballyholme: EXCELLENT @ 28th-Aug Ballywalter: GOOD @ 28th-Aug Castlerock: EXCELLENT @ 28th-Aug Clogherhead: EXCELLENT @ 27th-Aug Enniscrone: POOR @ 30th-Aug Lady's Bay: POOR @ 29th-Aug Newcastle: EXCELLENT @ 30th-Aug Portrush (curran): EXCELLENT @ 30th-Aug Waterfoot: EXCELLENT @ 30th-Aug

click for map view Information based on real water quality test results



Mobile App



3. Model Refinement

Predictor Variable Response Variable MERA Historical Data WQ Samples Model Training / Testing + additional variables + additional WQ samples HARMONIE Compliance Data Samples Model Implementation (Predictions)

Key Challenge

Lack of Historical Observed Water Quality Data (2007 – 2018)

- Total Water Quality Samples: 560 to 130 (most sites ~ 300)
- Poor Water Quality Samples: 40 to 2 (most sites ~ 20 to 30)
- Relatively high proportion of non-meteorologically driven "Poor" samples (~ 20% to 30% at some sites)
- Impact:
 - Too few samples to adequately train the model at some sites.
 - Model is highly sensitive to the train / test split at other locations.
 - Model is confounded by non-meteorologically driven events.
 - ✓ Dogs, Birds, Horses, etc...

Non-Meteorologically Driven WQ Failures can't be predicted (by this type of model)





https://barkpost.com/life/17-dogs-who-willshamelessly-ruin-your-beach-day/





Model Development – Next Steps

Multi-Model Development Framework

- A wide range of non-linear classification and tree-based methods are available which can utilize multi-variate data (e.g. MERA, rain radar, tide).
- A framework for training and testing multiple different models in parallel is under development – utilizing the "Caret" package in R, which contains ~ 240 different machine leaning models.

Discriminant Vector **No Free Lunch Theorem** Analysis Machines Neural K-Nearest Networks Neighbors "There is no such thing as a Non-Linear Non-Linear Classification single, universally-best Discriminant Naïve Bayes Analysis machine learning algorithm, **Classification Models** and there are no context or Basic usage-independent (a priori) C5.0 Classification Trees **Classification Trees &** reasons to favor one **Rule Based Models Rule Based** algorithm over all others." Boosting Methods Random **Bagged Trees** Forests

Flexible

Support







MÉRA Variables

Variable	Units	Variable Type	Location	Temporal Aggregation*	Variables @ Newcastle
Precipitation	mm	Numeric	Catchment	Sum	138**
Soil Moisture	kg/m ³	Numeric	Catchment	Mean	138**
Temperature	°C	Numeric	Sample Point	Mean	6
Atmospheric Pressure	kPA	Numeric	Sample Point	Mean	6
Direct Normal Irradiance	kW/m ²	Numeric	Sample Point	Sum	6
Wind Speed	Beaufort scale	Categorical	Sample Point	Mean	6
Wind Direction	Cardinal Direction	Categorical	Sample Point	Mode	6

* Data was aggregated over periods of 1, 6, 12, 24, 48, and 96 hours from the time of the sample.

** 22 MERA Points in Newcastle Catchment + 1 Catchment Mean x 6 Time Aggregations = 138 variables

Modelling Flowchart



Sensitivity / Specificity Trade-Off

There is typically a trade-off between model **sensitivity** and **specificity**, and increasing one results in a decrease in the other.





Specificity

Bathing Water Quality models typically achieve high **specificity**, while high **sensitivity** is more difficult to achieve.

This is due to the relatively low frequency of WQ failures (at most sites), complex driving conditions, and the occurrence of non-meteorological drivers.

High False Alarms

Model Performance Standards: Sensitivity & Specificity

Source	Sensitivity	Specificity
Thoe et al. (2014) "Predicting water quality at Santa Monica Beach: Evaluation of five different models for public notification of unsafe swimming conditions"	>30%	>80%
California's "Nowcast" System https://beachreportcard.org/	>50%	>85%
Scottish EPA <i>R. Stidson, personal communication</i>	>50%	-
UK Environment Agency D. Tyrell, personal communication	Scoring System of Criteria	Using a Range a (0 – 30)

Following the levels set out by these standards, in our models we seek to maximize *sensitivity* while maintaining a minimum *specificity* of 0.80.

Example of Model Performance at Different Thresholds



Newcastle			1.0 -
Threshold	Sensitivity	Specificity	0.8
None	0.00	1.00	
19 mm 2 days	0.17	0.98	0.6
8 mm 1 day	0.37	0.95	
6 mm 1 day	0.49	0.89	
4 mm 1 day	0.51	0.87	0.2
7 mm 2 day	0.57	0.82	0.0
			0.00 0.05 0.10 0.15 0.20 False Alarm Rate (1 - Specificity)