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A generic approach for the development of short-term predictions of *E. coli* and biotoxins in shellfish

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Abstract: Microbiological contamination or elevated marine biotoxin concentrations within shellfish can result in temporary closure of shellfish aquaculture harvesting, leading to financial loss for the aquaculture business and a potential reduction in consumer confidence in shellfish products. We present a method for predicting short-term variations in shellfish concentrations of *Escherichia coli* (*E. coli*) and biotoxin (okadaic acid, its derivates dinophysistoxins and pectenotoxins). The approach is evaluated for two contrasting shellfish harvesting areas. Through a meta-data analysis and using environmental data (*in situ*, satellite observations and meteorological nowcasts and forecasts) key environmental drivers were identified and used to develop models to predict *E. coli* and biotoxin concentrations within
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shellfish. Models were trained and evaluated using independent datasets and the best models were identified based on the model exhibiting the lowest root mean squared error (RMSE). The best biotoxin model was able to provide one-week forecasts with an accuracy of 86%, a 0% false positive rate and a 0% false discovery rate \((n = 78\) observations) when used to predict the closure of shellfish beds due to biotoxin. The best \(E.\ coli\) models were used to predict the European hygiene classification of the shellfish beds to an accuracy of 99% \((n = 107\) observations) and 98% \((n = 63\) observations) for a bay (St Austell Bay) and an estuary (Turnaware Bar), respectively. This generic approach enables high accuracy short-term farm-specific forecasts, based on readily accessible environmental data and observations.

**Keywords:** aquaculture; modelling; forecast; shellfish; water quality

1. **Introduction**

Aquaculture plays a major role in meeting the demand in seafood production and with the decline of wild fish stocks (FAO 2005), production is expected to grow further (Kobayashi et al. 2015). In Europe, shellfish aquaculture, produced 632,000 tonnes of bivalves in 2014 and this constituted 25% of the total European marine and coastal aquaculture production (FAO 2016). The sustainability of shellfish farming businesses can be compromised by events of poor water quality due to either microbiological contamination or naturally occurring marine phytoplankton producing biotoxins, both of which can cause temporary closures of shellfish aquaculture harvesting. Frequent or sustained events can often determine the success or failure of an aquaculture business. Furthermore, closure due to poor water quality has been shown to influence the confidence of consumers in shellfish products (Lucas &
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Southgate 2012). In the European Union shellfish harvesting areas are required to be classified according to their sanitary quality, on the basis of *Escherichia coli* (*E. coli*) monitoring in shellfish flesh (EU 2015). The classification determines the likely contamination with viral and bacterial pathogens and determines the extent of post-harvest processing required, before shellfish can be placed on the market for human consumption. Similar monitoring occurs in many other parts of the world (Rees et al. 2010). Increased *E. coli* concentrations in coastal or estuarine water bodies are often related to direct water run-off from urban and agricultural land, or due to sewage overflow entering the water body (Defra 2011). As a result, environmental factors such as rainfall, river flow and solar radiation can amplify or modulate the abundance and distribution of *E. coli* in shellfish waters (Kelsey et al. 2004, Coulliette et al. 2009, Kay et al. 2010).

Some naturally occurring phytoplankton can produce a range of marine biotoxins (Hinder et al. 2011) and once filtered by shellfish the biotoxins are retained and hence pose a health risk to humans when the shellfish are consumed (Anderson 2014). Therefore, farmed shellfish are also monitored for biotoxins and once a threshold concentration within the shellfish is exceeded, the harvesting area is closed (EU 2011). One important phytoplankton genus known to produce the biotoxin okadaic acid, its derivates dinophysistoxins and pectenotoxins (OA/DTX/PTX) is *Dinophysis* (Reguera et al. 2012). This group of toxins can cause gastrointestinal illness (Diarrhetic Shellfish Poisoning) in humans even when the density of causative organisms is low (Reguera et al. 2012). Production of toxin in *Dinophysis* cells is influenced by intrinsic and genetic factors as well as by the response of the species cells to environmental conditions, e.g. physical, chemical and biological factors (Reguera et al. 2012, Anderson 2014, Whyte et al. 2014, Gobler et al. 2017).
Whilst elevated *E. coli* or biotoxin concentrations within shellfish can cause temporary closure of the farm and restrictions on sales, the shellfish themselves are unharmed. Furthermore, leaving the shellfish living in the water allows the contaminants to depurate and dissipate naturally (Egmond et al. 2004, Davidson et al. 2011). Once this has occurred the shellfish farm and harvesting is re-opened and all stock can be safely sold and consumed. However, once harvested it is often not economically viable, or dependent upon the farm type even feasible, to return the live shellfish to the farmed waters (Morgan et al. 2009, Berdalet et al. 2015). Therefore, any information to guide farm decisions about when to harvest, when not to harvest and when to sell existing harvested stock at wholesale prices can be beneficial to the farm.

Whilst previous studies related environmental conditions, such as rainfall to *E. coli* or biotoxin concentrations (e.g. Kay et al. (2010)), the use of models to predict concentrations within shellfish has been limited (e.g. Bougeard et al. (2011)). This study identifies key environmental drivers of *E. coli* and biotoxin concentrations within the shellfish in two different shellfish harvesting areas. This information is then used to create short-term (one week) forecast models, with the intention that the forecast could be used to inform and support farm management decisions.

2. **Study areas and data collection**

2.1. **Coastal bay - St Austell Bay, UK**

St Austell Bay (Figure 1) is located on the south coast of Cornwall, United Kingdom and covers approximately an area of ~ 21 km², with mean depth ranges of 5 m near the shore to 20 m at the mouth (Sherwin & Jonas 1994, Sherwin et al. 1997). The bay is characterised by very small tidal currents (about 0.024 m s⁻¹) and the
circulation within the bay is driven by wind and density effects, with a mean eastwards circulation of ∼ 0.06 m s⁻¹ (Sherwin & Jonas 1994). Thermal stratification occurs during calm wind conditions (less than 5 m s⁻¹) (Sherwin et al. 1997). The river Par and other smaller streams entering the bay have been noted in the past to influence the near-shore dynamics of the bay (Sherwin et al. 1997). Within the bay two shellfish farms cultivate blue mussels (*Mytilus* spp.) on ropes and both are classified as class B under European hygiene classification (EU 2004a).

2.2. Estuary – Turnaware Bar within the lower Fal estuary, UK

The sheltered Fal estuary is situated at the south coast of Cornwall, United Kingdom and covers an intertidal area of 0.46 km² (ABPmer & Wallingford 2007). The estuary can be distinguished into two geographical areas (Upper and Lower Fal) and this study focused on Turnaware Bar (Figure 1), which is within the lower Fal estuary. For more than two centuries, native oysters (*Ostrea edulis*), mussels (*Mytilus* spp.) and Pacific oysters (*Magallana gigas*) have been commercially harvested from this estuary. Under European hygiene classification the bivalve molluscs production area at Turnaware Bar is classified as class B (EU 2004a).

2.3. Data collection and processing

2.3.1. *Escherichia coli* (*E. coli*)

Following European legislation concentrations of β-glucuronidase-positive *Escherichia coli* (*E. coli*) in shellfish (mussels and oysters) are routinely monitored in both study sides. The *E. coli* data were collated for St Austell Bay (sampling site Ropehaven) and Turnaware Bar, for the period 2008 – 2016 and 2011 – 2016, respectively (table 1). *E. coli* is determined using the enumeration method ISO
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122 16649-3 (ISO 2015) and concentrations are reported as most probable number
123 (MPN) of *E. coli* 100 g\(^{-1}\) of flesh. Therefore concentration values at the lower limit of
124 quantification of the MPN method (< 20 MPN 100 g\(^{-1}\) and from 2015 onwards < 18
125 MPN 100 g\(^{-1}\)) were adjusted to 19 MPN 100 g\(^{-1}\) and 17 MPN 100 g\(^{-1}\), respectively as
126 recommended by the US National Shellfish Sanitation Program (USFDA & ISSC
127 2013, 2015). The expanded uncertainty of the *E. coli* MPN method has been
128 estimated at 0.66 (of the log\(_{10}\) MPN 100 g\(^{-1}\) transformed data), which is calculated as
129 twice the measured standard deviation (SD) (Baker-Austin et al. unpubl. data).

2.3.2. Biotoxin

130 Shellfish samples for St Austell Bay are routinely analysed for the group biotoxin,
131 okadaic acid (OA) and its derivates, dinophysistoxin (DTX) and pectenotoxin (PTX)
132 using liquid chromatography coupled with mass spectrometry as described by Cefas
133 (2011). This biotoxin group is reported in μg OA equivalent (eq.) kg\(^{-1}\) shellfish flesh
134 and the Food Standard Agency (FSA) regulatory monitoring data were obtained from
135 Cefas for the time period from 2014 to 2016 (table 1). The minimum reporting limit of
136 the analysis method is stated as 16 μg OA eq. kg\(^{-1}\) shellfish flesh (EU 2004b, c) and
137 so values within the dataset below this reporting limit were adjusted to 15 μg OA eq.
138 kg\(^{-1}\) shellfish flesh.

2.3.3. Environmental datasets

141 A metadata analysis identified that the following variables were important for
142 controlling *E. coli* and biotoxin concentrations within shellfish (rainfall, river flow, solar
143 radiation, sea surface temperature (SST), wind speed and direction (Šolič &
145 Defra 2011, Reguera et al. 2012, Campos et al. 2013). Therefore, a suite of
environmental data was collated to allow the linkages between the environmental
conditions and the *E. coli* and biotoxin concentrations in shellfish to be investigated.

Daily rainfall measurements (mm day⁻¹) at Luxulyan (for St Austell Bay) and St
Mawes (for Turnaware Bar) were obtained from the UK Environment Agency (EA) for
2008 - 2016. The rainfall on the day prior to shellfish sampling (lag rainfall) was
included as an additional variable. River flow measurements (m s⁻¹) of the major
rivers (Par river for St Austell Bay; Fal, Carnon, Kennall, Kenwyn and Allen river for
Turnaware Bar, Figure 1) were obtained from the EA for 2008 - 2016. Due to the
multiple river sources, the sum of the river flow of the rivers entering the lower Fal
estuary was calculated and used for the statistical analysis for Turnaware Bar.

Reanalysed meteorological forecast data (10 m U wind, 10 m V wind in m s⁻¹ and
downwards surface solar radiation in J m⁻²) were downloaded from the ERA-Interim
archive for 2008 to 2015 from the European Centre for Medium-Range Weather
Forecast website (http://apps.ecmwf.int/datasets/) (Berrisford et al. 2011). The data
for the two study sites were then extracted from the nearest model grid point (St
Austell Bay: latitude 49.50; longitude 356.25 and Turnaware Bar: latitude 49.50;
longitude 354.75). Daily 10 m U wind and 10 m V wind instantaneous data at 00, 06,
12, 18 Coordinated Universal Time (UTC) were used to calculate the daily mean
wind speed and direction. Daily surface solar radiation at 00 and 12 UTC were
extracted and added to determine total surface solar radiation per day. Satellite SST
observations were obtained for both study sites for 2008 - 2016. The Multi-scale
Ultra-high Resolution (MUR) dataset from NASA Jet Propulsion Laboratory
(http://mur.jpl.nasa.gov/) were used to ensure that data were always available (even
in cloudy conditions). These data are a daily, 1 km resolution dataset consisting of a
combination of infrared and passive microwave based sensor observations. The
mean values between latitude 50.28 and 50.31, and longitude -4.69 and -4.75 were extracted for St Austell Bay, and between latitude 50.12 and 50.13, and longitude -5.02 and -5.13 for Turnaware Bar (Figure 1). Any pixels defined as land within the MUR land mask were excluded from the analysis.

For the independent evaluation of models and to predict *E. coli* and biotoxin concentrations, near-real time and now cast environmental data for 2016 for both sites were obtained by the EA, extracted via the MARS ECMWF website (http://apps.ecmwf.int/mars-catalogue/) and satellite data were extracted as described above. The selected dates were chosen to coincide with the official control monitoring results for *E. coli* and biotoxin concentrations tested in shellfish by the FSA and Cefas.

3. Environmental drivers for *E. coli* and biotoxin concentrations

3.1. Statistical approaches for a suite of models

All data exploration and modelling analyses were conducted using the R statistical software (version 3.3.0 on Mac ODS X 10.10.3, (R Core Team 2016)).

The collated datasets (section 2) were all split into two, based on two time periods. The first dataset was used for model development and initial characterisation of the models. The second dataset was used to provide an independent evaluation of model performance. The details of the dataset splitting are provided in table 1.

3.1.1. Generalized Linear Model development

Due to non-Gaussian nature of the response variables (concentrations of OA/DTX/PTX and *E. coli*), they were log transformed prior to use (Kay et al. 2008).

Four Generalized Linear Models (GLMs) were developed using the function
bestglm() in R. Four different cross-validation methods were used to determine the optimal model (McLeod & Xu 2014). These were i) R’s default option deleted-d cross-validation with random subsamples using the delete-d algorithm \( d = \text{ceil}(n(1-1/(\log n - 1))) \) and \( t = 10 \) repetitions, where the parameter \( d \) is chosen using the formula recommended by Shao (1997); ii) K-fold cross validation (Hastie et al. 2009); iii) adjusted K-fold cross validation (Davison & Hinkley 1997) and iv) leave-one-out cross-validation approach. To compare the performance of the four GLMs to each other, the root mean square error (RMSE) was calculated. The output from R provides a list of the significant explanatory (predictor) variables.

3.1.2. Averaged GLM development

The model-averaging GLM based on the information-theoretic approach by Burnham and Anderson (2002) was calculated. Firstly, a ‘global model’ was built, using the glm() function with all environmental factors as dependent variables. In order to directly compare the global model’s independent variables, the model was then standardised (mean = 0 and SD=0.5). The dredge() function within the R package ‘MuMIn’ (Bartoń 2015) enabled the generation and comparison of all possible models and the best performing models, used to construct the model-averaged result, were selected using delta Akaike Information Criterion < 2 as the decision metric. Using the variance inflation factors, the averaged model was tested for potential co-linearity between covariates. Where correlated covariates existed, only one variable was retained (Zuur et al. 2010).

3.1.3. Generalized Additive Model development

The gam() function in the R package ‘mgcv’ (Wood 2006) was used to develop the Generalized Additive Model (GAM). Initially all explanatory variables were set as
smooth terms and knots were set manually to four as the number of observations were < 100 (Thomas et al. 2015). The estimated degrees of freedom of the smoothed term was used to check the GAM model assumptions and the model terms were then adjusted to be linear terms in cases where estimated degrees of freedom equalled 1 (Thomas et al. 2015).

3.2. Independent evaluation of all models

An independent comparison is recommended for model evaluation (Verbyla & Litvaitis 1989, Fielding & Bell 1997). Therefore, the accuracy of each model (the best GLM based on its lowest cross-validation RMSE, the best averaged GLM, and the GAM) was evaluated using their respective evaluation datasets (table 1) by calculating the RMSE and bias between the predicted and the actual observed E. coli and biotoxin concentrations. The limits and uncertainties in their analytical detection have been described in section 2.3.1 and 2.3.2. The best model was identified as the model that produced the lowest RMSE. A confusion matrix analysis was then used to understand how the model accuracy (RMSE and bias) translates to the ability to answer specific management questions. This analysis allows the determination of the accuracy, precision, false positive rate and false discovery rate, which could have significant impacts on an aquaculture business (Stehman 1997). The confusion matrix was used to determine i) the best E. coli model’s capability to predict the EU shellfish bed classification (which is class B for both sites, see section 2.1. and 2.2.) and ii) the best biotoxin model’s ability to predict the closure and re-opening of shellfish harvesting based on the regulatory threshold of 160 μg OA eq. kg⁻¹ shellfish flesh.

4. Results and discussion
4.1. Models for E. coli concentrations in St Austell Bay and Turnaware Bar

The observed and modelled E. coli concentrations can be seen in figure 2. Both study sites displayed low observed E. coli concentrations over the year 2016, with mean of 1.54 log₁₀ E. coli 100 g⁻¹ of flesh for St Austell Bay and of 2.23 log₁₀ E. coli 100 g⁻¹ of flesh for Turnaware Bar (table 2). Observed E. coli concentrations were generally below class A limit in St Austell Bay (class A requirements are 80% of samples must not exceed 230 E. coli 100 g⁻¹ of flesh and the remaining 20% of samples must not exceed 700 E. coli 100 g⁻¹ of flesh). Only one result during the winter of 2016 exceeds the class A limit of E. coli 100 g⁻¹ of flesh (figure 2; on 2nd Feb 2016). A slightly larger variability in observed E. coli concentrations is apparent at Turnaware Bar (figure 2).

All three model outputs (GLM, average GLM and GAM) fitted the observed E. coli concentrations reasonably well. Statistical measures for observed (mean, standard deviation) and modelled (RMSE, bias) E. coli concentrations in St Austell Bay and Turnaware Bar are listed in table 2. For both study areas, the GLM model showed the lowest RMSE (St Austell Bay: 0.48 log₁₀ E. coli 100 g⁻¹ shellfish flesh; Turnaware Bar: 0.68 log₁₀ E. coli 100 g⁻¹ shellfish flesh (table 2)).

4.2. Environmental drivers for E. coli concentrations in St Austell Bay and Turnaware Bar

Significant explanatory variables used for predicting E. coli concentrations for each model and both study sites are summarised in table 3. The majority of models...
identified rainfall and/or lag rainfall as one of the key explanatory variables for predicting E. coli concentrations (table 3).

Rainfall has been previously described as a common environmental factor associated with controlling E. coli concentrations in receiving waters (Kelsey et al. 2004, Coulliette et al. 2009, Kay et al. 2010, Campos et al. 2013). However, the degree of response of E. coli concentrations to rainfall can vary considerably between sampling points in a given sampling area (Defra 2011), which can be attributed to differences in land use (e.g. agriculture run-off versus urban sewage) and soil conditions surrounding the sampling site (Kay et al. 2010, Defra 2011). In all models for Turnaware Bar, river flow was identified as significant and this catchment has been previously described as highly responsive to rainfall (Cefas 2012). River flow may also provide a proxy for other events contributing to faecal contamination (e.g. combined sewer overflows, application of slurry to fields, etc.) and therefore it is not possible to explain the direct cause for the varying E. coli concentrations. Turnaware Bar, the study point within the lower Fal estuary, is exposed to a lower ‘flushing’ time due to tides and thus resulting in a potentially higher retention time of microbial contamination from nearby sources (Uncles et al. 2002, Langston et al. 2006).

For St Austell Bay, solar radiation was identified as an important explanatory variable for predicting E. coli concentrations (table 3). All models displayed the solar radiation term as negative and this is consistent with previous work by Campos et al. (2013) that showed that solar radiation can influence the die-off of E. coli in seawater. Additionally, Šolić and Krstulović (1992) suggested that solar radiation may be more important than seawater temperature in altering the number of the faecal indicator. However, for Turnaware Bar all three models identified SST as a key explanatory
variable. Although *E. coli* optimal growth temperature lies at around 37 °C, it has been previously shown that the optimal temperature for survival is not necessarily the same as that needed for optimal growth (Rozen & Belkin 2001) as *E. coli* can survive and stabilise at lower temperatures within estuaries (Rhodes & Kator 1988).

4.3 Ability to predict shellfish bed classification

Using easily attainable environmental measurements to predict the shellfish *E. coli* concentrations would enable local authorities to estimate the likely variation in *E. coli* within a shellfish area, in the absence of regular monitoring e.g. if shellfish beds are currently not used, but are available for lease. Therefore, the confusion matrix allowed the overall performance (termed accuracy) and precision (if predicted class B, how often was the model correct) to be calculated for both sites, using the best *E. coli* model (the model with the lowest RMSE).

The overall accuracy for St Austell Bay was 99 % determined using data from 2008 to 2016 (n = 107); 100% for data from 2016 only (n = 13)). Additionally, the precision was 100 % for data from 2008 to 2016 (n = 107) and 100% for data from 2016 (n= 13)).

Similarly, results for Turnaware Bar showed a high accuracy of 98% for data from 2011 to 2016 (n = 63) and 100 % using data from 2016 only (n = 10)), with a precision of 100 % (2011 - 2016, n=63) and 100 % for just 2016 (n = 10).

It is noted, that despite the use of long-term datasets (St Austell Bay: 9 years; Turnaware Bar: 5 years) relatively limited variations in *E. coli* are apparent.

4.3. Models for biotoxin concentrations in St Austell Bay

The observed and modelled biotoxin concentrations can be seen in figure 3. During 2016 the observed biotoxin concentrations ranged from below the reporting limit up
to 2013 μg OA eq. kg\(^{-1}\) shellfish flesh. Between mid July and end of October, the observed biotoxin concentrations were above the maximum permitted level of 160 μg OA eq. kg\(^{-1}\) shellfish flesh (EU 2011), indicated as the red horizontal line within figure 3, and therefore the shellfish farm was closed for this period.

Table 4 lists statistical measures for observed (mean, standard deviation) and modelled (RMSE, bias) biotoxin concentrations. The averaged GLM produced the lowest RMSE (582.3 μg OA eq. kg\(^{-1}\) shellfish flesh), whereas the GAM showed the lowest bias of -71.01 μg OA eq. kg\(^{-1}\) shellfish flesh.

All three models were consistent to capture the increase and reduction of biotoxin concentrations within the shellfish (i.e. the points at which concentrations increase and decrease in relation to the legal limit, figure 3). However, all models showed differences in their response when modelling the period between the ‘accumulation’ and ‘depuration’ phases. The depuration of biotoxin concentrations within the shellfish depends upon the species and the physiological conditions of the shellfish e.g. fat content, respiration state, growth, food availability etc. (Hallegraeff 1995). No physiological parameters, describing the depuration of the group biotoxin OA/DTXs/PTXs in blue mussels, were found in the published literature and thus it was not possible to identify specific depuration parameters for the model development. Future studies describing the toxicological profile of OA/DTXs/PTXs in blue mussels would therefore be beneficial.

4.5. Modelling biotoxin accumulation and depuration phases in St Austell Bay

To investigate the difference between accumulation and depuration of the biotoxin, the models were retrained using either only accumulation data (n = 27 observations from 2014 & 2015) or only depuration data (n = 27 observations from 2014 & 2015).
The ‘accumulation’ phase was defined as the beginning of the year to the highest observed biotoxin concentrations, while the ‘depuration’ phase was defined as from the highest observed concentration to the end of the year.

The accumulation models showed higher RMSE (GLM = 1745.73; averaged GLM = 858.33; GAM = 1151.99) than the models trained on the full dataset (section 4.2) when evaluated using the full evaluation dataset (table 4). Similarly, the depuration models also showed a higher RMSE (RMSE for GLM = 868.39; averaged GLM = 110.29; GAM = 17,965.03) and both models were unable to capture the appropriate response of the biotoxin concentration. This result supports the usage of the model trained on the full dataset in order to forecast biotoxin concentrations and highlights that different environmental and physiological factors are controlling the accumulation and depuration phase.

4.6. Ability to predict farm closure and reopening due to biotoxins

The ability for a farm to identify the potential closure due to accumulation of biotoxins in mussels is advantageous for supporting decisions on harvesting and sales (e.g. when to sell existing stock at wholesale prices). Therefore, the performance of the model with the lowest RMSE (averaged GLM) trained on the full dataset (table 1 & 4) to accurately forecast the closure of a shellfish farm was evaluated. The overall performance (accuracy), false positive rate (false prediction of an open farm, when it should actually be closed) and false discovery rate (error in predicting the opening and closure of the farm) were calculated.

The nowcast predictions (n = 79 observations for 2014 - 2016) of the confusion matrix produced an accuracy of 84 % with a false positive rate of 2 % and false discovery rate of 4 %. Results using data from just 2016 showed a higher accuracy.
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(92 %) with a false positive rate of 6 % and a false discovery rate of 13 % (n = 25 observations).

For a one-week forecast (n = 78 observations for 2014 - 2016) the accuracy was 86 % with a false positive rate of 0 % and false discovery rate of 0 %; in comparison results for the one-week forecast using just 2016 data showed an accuracy of 96 %, with a false positive rate of 0 % and false discovery rate of 0 % (n = 24 observations).

4.5. Environmental drivers for biotoxin concentrations in St Austell Bay

Environmental variables such as SST, solar radiation and wind speed were identified as key drivers for the different biotoxin models (table 5). Additionally, other environmental variables, including lag rainfall and wind direction contributed to some of the models.

Previously, it has been shown that the ambient temperature influences the filtration rate and pumping activity in blue mussels (Jørgensen et al. 1990). The distribution and occurrence of the dinoflagellate genus *Dinophysis* spp. in the water column in temperate regions can be related to stratification of water column (Raine & McMahon 1998). Seawater temperature, salinity and dissolved oxygen concentrations were recorded in close proximity of the shellfish farm from autumn 2015 until summer 2016 using a moored buoy (Schmidt et al. 2018). Figure 4 shows that the SST just outside of the farm increased by around of 2°C at 1.1 m depth from 2nd to 8th July 2016, indicating that thermal stratification could have taken place within the farm in July (e.g. as the farm itself is likely to accelerate stratification by dampening vertical mixing). In addition, step increased of dissolved oxygen concentrations (green line within Figure 4) from 5th to 7th July 2016 indicates an increase of biological activity close to the farm site. This period would coincide with the closure of the farm on the
5th July 2016 due to high biotoxin concentrations (indicated as red vertical line within Figure 4). These observations support the hypothesis (Farrell et al. 2012) that increased abundance of *Dinophysis* spp. in the water column can be related to thermal stratification. However, a future study would need to confirm this by placing the instruments within the mussel farm ropes.

A further important factor influencing the distribution of *Dinophysis* spp. can be its transport by ocean currents from offshore locations into coastal bays (Escalera et al. 2010). Raine et al. (2010) suggested that wind driven water exchange between the south coast of Ireland and the continental shelf is responsible for an influx of *Dinophysis* spp. into a shellfish harvesting area. Large scale wind driven advective processes were also proposed by Whyte et al. (2014) to explain large coastal blooms of *Dinophysis* spp. in the Shetland Islands. All three biotoxin models identified wind speed as a key environmental factor for the shellfish biotoxin concentration. However, no significant correlation was found between increased biotoxin concentrations and wind speed or direction. As a third key environmental driver, solar radiation, was identified as an important factor by the models. Toxicological profiles of DSP toxin reported that its synthesis requires light and is coupled to the cell division cycle (Pan et al. 1999). This again supports the hypothesis that stratification is important, as stratification will imply reduced turbidity and therefore an improved light field within the water column.

This study chose to focus on OA/DTXs/PTXs toxin as these were a significant issue for the shellfish farmer in St Austell Bay. Mussels were the focus shellfish as these dominate the global bivalve production and they can be used as indicator species for monitoring other bivalve production. Clearly the generic nature of the approach means that it could be applied to other toxin groups (e.g. PSP, ASP, AZA) if sufficient
data to train and evaluate the models exists. However for our study site and temporal period (2014 - 2016) neither PSP nor ASP have exceeded the maximum permitted limit and there was only three instances of AZA exceeding the permitted limit. Therefore, we were unable to test the applicability to other toxin groups.

5. Conclusion

This study has demonstrated that a generic approach and a suite of readily available environmental data (in situ, satellite observations and meteorological nowcasts and forecasts) can be used to successfully model the E. coli concentrations within shellfish living in an estuarine and coastal shellfish site, despite the sites exhibiting contrasting hydrography. The same methodology has then been shown to successfully model the biotoxin concentrations within shellfish living in a coastal shellfish site. The accuracy of models have been evaluated and characterised using data independent to the training data, and indirectly verified using measurements from an in situ monitoring buoy located close to one of the sites. The inputs to these models were identified by a metadata analysis as being important for influencing the E. coli and biotoxin concentrations within shellfish and the parameters identified as significant by each model analysis are consistent with previous studies.

Whilst the models were less able to accurately predict the absolute values of the concentrations within the shellfish, the modelled variations in E. coli and biotoxin concentrations have been demonstrated to be reliable for supporting farm decision marking. Accurate classifications of a change in shellfish bed class and forecasting closure due to biotoxin accumulation were both possible. The biotoxin models can be used to provide a one-week forecast. Such an early warning can provide and support the shellfish farmers in their management by guiding harvesting decisions and pricing.
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strategies. Using these forecasting approaches is also likely to help increase customer confidence in shellfish products, and give farmers increased confidence when selling their product. After initial model development for a harvesting site, the shellfish farmer could use this approach and the subsequent models to forecast changes within their farm shellfish stock, towards supporting farm management decisions. However, it is likely that a yearly update of the model parameters would be needed to account for temporal changes in the catchment, regional climate, changes to farm composition and size, and influences that the farm itself will have upon the local ecosystem.

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References

Short-term predictions for shellfish aquaculture


Cefas (2011) In-house validation of an LC-MS/MS method for the determination of lipophilic toxins in shellfish species typically tested in the United Kingdom. In:


Short-term predictions for shellfish aquaculture


Short-term predictions for shellfish aquaculture

523  gastropods and Annex I to Regulation (EC) No 2073/2005 on microbiological
524  criteria for foodstuffs. Official Journal of the European Union 58
525  FAO (2005) Review of the state of world marine fishery resources. FAO FISHERIES
526  TECHNICAL PAPER 457
528  security and nutrition for all. In, Rome, Italy
530  (2012) Scales characterising a high density thin layer of Dinophysis acuta
531  Ehrenberg and its transport within a coastal jet. Harmful Algae 15:36-46
533  errors in conservation presence/absence models. Environmental Conservation
534  24:38-49
536  (2017) Ocean warming since 1982 has expanded the niche of toxic algal blooms in
537  the North Atlantic and North Pacific oceans. Proceedings of the National Academy
538  of Sciences 114:4975-4980
541  UNESCO
543  2nd Ed. Springer-Verlag
Short-term predictions for shellfish aquaculture


Kelsey H, Porter DE, Scott G, Neet M, White D (2004) Using geographic information systems and regression analysis to evaluate relationships between land use and
Short-term predictions for shellfish aquaculture


582 R Core Team (2016) R: A language and environment for statistical computing. In: Computing RFfS (ed), Vienna, Austria

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Figure 1. Location of St Austell Bay (C), Turnaware Bar (D), river gauge stations, in situ buoy within St Austell Bay (blue triangle) and data extraction areas for satellite sea surface temperature (dotted boxes, St Austell Bay: E; Turnaware Bar: F).
Figure 2.

Modelled and observed concentrations of *E. coli* in 1. St Austell Bay and 2. Turnaware Bar for the year 2016. All *E. coli* concentrations are displayed as $\log_{10} E. \ coli$ 100 g$^{-1}$ shellfish flesh. Modelled concentrations (green line ± model standard error in shaded green) were obtained by A) GLM, B) averaged GLM and C) GAM. Observed *E. coli* concentrations are shown with a line with triangles (blue line ± uncertainty of 0.66 (2 x SD) in shaded blue). The dashed and dotted black line indicates the limit of class A classification for shellfish bed (dashed = $\log_{10}$ 230 *E. coli* 100 g$^{-1}$ shellfish flesh for 80% samples; dotted = $\log_{10}$ 700 *E. coli* 100 g$^{-1}$ shellfish flesh for 20% samples), whereas the solid black line represents the upper limit of class B classification ($\log_{10}$ 4,600 *E. coli* 100 g$^{-1}$ shellfish flesh).
Figure 3. Modelled and observed biotoxin concentrations St Austell Bay for the year 2016. All biotoxin concentrations are displayed as μg OA eq. kg\(^{-1}\) shellfish flesh. Modelled concentrations (green line ± model standard error) were obtained by A) GLM, B) averaged GLM and C) GAM. Observed biotoxin concentrations are shown in line with triangle (blue line = high measurement uncertainty (MU) values, blue shade = low MU values). The red line indicates the maximum permitted level of 160 μg OA eq. kg\(^{-1}\) shellfish flesh at which point the farm is closed.
Figure 4. *In situ* data from monitoring buoy from 1\textsuperscript{st} June to 22\textsuperscript{nd} July 2016; a SST sensor at 1.10 m, a salinity sensor at 1.25 m (blue line with circle) and an oxygen sensor at 1.65 m (green line). The monitoring buoy was located in close proximity to the shellfish farm and its design is described in (Schmidt et al. unpubl. data). Vertical red line indicates the date (5\textsuperscript{th} of July 2016), when the shellfish farm was closed due to high biotoxin concentrations (> 160 μg OA eq. kg\textsuperscript{-1} shellfish flesh). The mean SST is shown as a black line with triangles (grey shading represents the minimum and maximum SST). The mean salinity is shown as a blue line with circles (light blue shading represents the minimum and maximum salinity) and the mean dissolved oxygen concentration is shown as a green line (light green shading represents the minimum and maximum concentrations).
Table 1. Overview of datasets used in the model development (Dev. dataset) and evaluation (Eval. dataset) for both study sites.

<table>
<thead>
<tr>
<th></th>
<th>St Austell Bay</th>
<th>Turnaware Bar</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Dev. dataset</td>
<td>Eval. dataset</td>
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<tr>
<td>E. coli observations</td>
<td>94</td>
<td>13</td>
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<tr>
<td>Biotoxin observations</td>
<td>54</td>
<td>24</td>
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</tbody>
</table>
Table 2. Comparison between modelled and observed *E. coli* for 2016 for both study sites. All values are presented as log_{10} *E. coli* 100 g^{-1} shellfish flesh. * = Best performing model

<table>
<thead>
<tr>
<th></th>
<th>St Austell Bay</th>
<th>Turnaware Bar</th>
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</thead>
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<tr>
<td></td>
<td>Observations</td>
<td>GLM*</td>
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<tr>
<td>Mean</td>
<td>1.54</td>
<td>1.92</td>
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<td>Standard deviation</td>
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<td>0.33</td>
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<td>RMSE</td>
<td>0.48</td>
<td>0.7</td>
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<tr>
<td>Bias</td>
<td>-1.54</td>
<td>0.61</td>
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### Table 3. Explanatory variables identified for *E. coli* models for St Austell Bay and Turnaware Bar.

<table>
<thead>
<tr>
<th>Model</th>
<th>Explanatory variables for <em>E. coli</em> in St Austell Bay</th>
<th>Explanatory variables for <em>E. coli</em> in Turnaware Bar</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLM</td>
<td>Lag rainfall* and solar radiation</td>
<td>River flow* and SST*</td>
</tr>
<tr>
<td>Averaged</td>
<td>Lag rainfall*, solar radiation*, rainfall, wind speed and SST*</td>
<td>River flow*, SST*, wind direction, solar radiation and rainfall</td>
</tr>
<tr>
<td>GLM</td>
<td>SST</td>
<td></td>
</tr>
<tr>
<td>GAM</td>
<td>Lag rainfall, solar radiation and as smoothed term: lag rainfall*</td>
<td>River flow*, SST* and as smoothed term: lag rainfall*</td>
</tr>
</tbody>
</table>

* Marked variables contributed significantly (p<0.05) to the model.
Table 4. Statistical measures for modelled and observed biotoxin concentrations in St Austell Bay for the year 2016, all values are presented as μg OA eq. kg\(^{-1}\) shellfish flesh. * = Best performing model.

<table>
<thead>
<tr>
<th>Observation/ Model</th>
<th>Statistical parameters</th>
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<tbody>
<tr>
<td></td>
<td>Mean</td>
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<tr>
<td>Observed data</td>
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<tr>
<td>GLM</td>
<td>227.61</td>
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<tr>
<td>Averaged GLM*</td>
<td>404.07</td>
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<td>GAM</td>
<td>443.7</td>
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Table 5. Explanatory variables identified for modelled biotoxin concentrations in St Austell Bay.

<table>
<thead>
<tr>
<th>Model</th>
<th>Explanatory variables for biotoxin in St Austell Bay</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLM</td>
<td>SST* and wind speed</td>
</tr>
<tr>
<td>Averaged GLM</td>
<td>SST*, solar radiation*, wind speed, lag rainfall and wind direction</td>
</tr>
<tr>
<td>GAM</td>
<td>SST*, solar radiation*, wind speed* and as smoothed term: lag rainfall</td>
</tr>
</tbody>
</table>

* Marked variables contributed significantly (p<0.05) to the model.