An approach for evaluating the economic impacts of harmful algal blooms:

Martino, Simone; Gianella, Fatima; Davidson, Keith

Published in:
Harmful Algae

Publication date:
2020

Citation for published version (APA):
Martino, S., Gianella, F., & Davidson, K. (2020). An approach for evaluating the economic impacts of harmful algal blooms: The effects of blooms of toxic Dinophysis spp. on the productivity of Scottish shellfish farms. *Harmful Algae*, *99*, Article 101912. https://doi.org/10.1016/j.hal.2020.101912

An Approach for Evaluating the Economic Impacts of Harmful Algal Blooms: the Effects of Blooms of Toxic *Dinophysis spp*. on the Productivity of Scottish Shellfish Farms

Simone Martino[1#], Fatima Gianella[2], Keith Davidson[2]

[1] University of York, Department of Environment and Geography, York, UK, YO10 5NG
E-mail: simone.martino@york.ac.uk
[2] Scottish Association for Marine Science, Oban, UK, PA37 1QA
E-mail: fatima.gianella@sams.ac.uk; keith.davidson@sams.ac.uk
#corresponding author

Highlights

- Economic impacts of harmful algae on Western Scottish shellfish aquaculture are assessed.
- The Cobb-Douglas production function is used to model these impacts.
- A 1% change in diarrhetic shellfish toxins is found to reduce production by 0.66%.
- Annual losses from *Dinophysis* generated biotoxins are estimated at 15% of total production (equivalent to £1.37 m/year in 2015 GBP).
- Such information is of use to industry to evaluate the cost/benefit of HAB mitigation measures.

Abstract

Shellfish production is an important activity for the economy of many countries. As well as its direct value, it helps to stabilize communities in rural areas characterized by limited job opportunities. It is also important for consumers who recognize shellfish as a healthy product that gains its nutrition from natural plankton without the need for fertilizers, chemical treatments or other anthropogenic intervention typical of terrestrial agriculture or other marine aquaculture. Nevertheless, global shellfish fisheries are under threat from harmful algal blooms (HABs) and related biotoxins, whose production is potentially exacerbated by global changes. This research provides evidence of economic impacts on Scottish shellfish farms in the last 10 years caused by HABs and their associated biotoxins. In contrast to previous approaches that have focused on variation in production as a function of temporal trends and blooms events, we use a production function approach to show which input factors (labour, capital, climate variables, concentration of biotoxins) have an effect on production. Results show that diarrhetic shellfish toxins produced by the genera *Dinophysis* are most significant. A 1% change in the production of these biotoxins reduces shellfish production by 0.66%, with an average yearly negative variation in production of 15% (1,080 ton) and an economic loss (turnover) of £ (GBP) 1.37 m per year (in 2015 currency) over a national annual industry turnover of ~ £ 12 m. The production function approach is coupled with a multivariate time series model (VAR) capturing the statistical relationship between algal concentration, information on climatic variables and biotoxins to forecast the damage to shellfish production from HABs. This provides producers and regulators with the economic information to plan temporal and spatial mitigating measures necessary to limit damages to production by comparing the costs of these measures with the costs of lost production.

1. Introduction

1.1 Background and aim of the study

Culture of bivalve molluscs is an important commercial activity in Europe, with a production of ~ 625k tonnes and value of EUR 1.24b in 2017 (European Union, 2019). Europe wide, mussel species exhibit the highest volume (35%) of farmed bivalves species, with a total EU production of 129,500 tonnes by 2017 (European Union, 2019). Shellfish farming is carried out predominantly by small family enterprises (STECF, 2018) and is important for many rural areas of Europe, including the Scottish Highlands where it generates a gross value (turnover) of £ 12.4m (Highlands and Islands Enterprise and Marine Scotland, 2017). In Scotland, it is undertaken by 205 separate enterprises generally located in rural coastal areas.

Blue mussels dominate shellfish production in Scotland (~ 96% by weight - MSS, 2018) with a value (turnover) of £ 10.1 m in 2017 (Highlands and Islands Enterprise and Marine Scotland, 2017; Munro and Wallace, 2018). The whole of Scotland’s shellfish aquaculture supply chain also contributes £ 25.9 m of associated earnings and £ 50 m of gross value added (average for 2014 and 2015) (Highlands and Islands Enterprise and Marine Scotland, 2017). While the value of the Scottish shellfish production in comparison with other industries is relatively small, its geographical location in remote communities characterized by few other employment opportunities makes it very important for the sustainable development of the rural economy. This is evident from the Scottish Government's support for the Scottish aquaculture industry's plans to double its economic value and the number of jobs it generates by 2030. However, to achieve this, it is important to have an accurate economic valuation of the different factors, such as harmful algal blooms (HABs), that are limiting current production and future expansion.

Globally, there is a positive market perception towards shellfish as an "environmentally healthy product" that gains its nutrition from natural plankton within the water column. This is because shellfish culture occurs without the need for fertilisers or chemical treatments typical of terrestrial agriculture or other marine aquaculture (Newell et al., 1989, Scotland's Aquaculture, 2020), with shellfish ingesting particulate matter in the water column. However, the mode of nutrition exhibited by these filter feeding bivalves makes them vulnerable to contamination by biotoxins produced by certain harmful algal species, with associated implications for human health (Smayda, 1990; Berdalet et al., 2016), but also for the economic sustainability of the industry (Davidson et al., 2014).

In Scottish waters Diarrheic Shellfish Poisoning (DSP), Paralytic Shellfish Poisoning (PSP) and Amnesic Shellfish Poisoning (ASP) are the shellfish toxicity syndromes of greatest concern (Davidson et al., 2011; Davidson and Bresnan, 2009). PSP toxins produced by the genus *Alexandrium* are regularly detected in mussels during the summer months (Bresnan et al., 2008). DSP toxins are more frequent still, often as a result of the advective transport of the causative *Dinophysis* to coastal aquaculture (Whyte et al., 2014; Paterson et al., 2017), with

Prorocentrum lima being another source of these toxins. *Pseudo-nitzschia* mediated ASP is less frequent (Rowland-Pilgrim et al., 2019) and may also require advective cells transport (Fehling et al., 2012). Azaspiracids (AZA) produced by the genus *Azadinium* (Tillmann et al., 2009) and yessotoxins (YTX) produced by the dinoflagellates *Protoceratium reticulatum* and *Lingulodinium polyedrum* also occur.

To ensure shellfish safety for public consumption, EU regulation EC No 853/2004 (European Union, 2004) requires the monitoring of the concentration of biotoxins in shellfish flesh and their causative harmful phytoplankton. In Scotland, monitoring is overseen by the competent authority Food Standards Scotland (FSS) and carried out by the Centre for Environment, Fisheries and Aquaculture Science (CEFAS) for biotoxins and the Scottish Association for Marine Science (SAMS) for phytoplankton. Sampling is undertaken weekly during spring and summer, and fortnightly in winter and autumn at a set of representative monitoring points with the aim of minimising the risk of not detecting above regulatory threshold shellfish biotoxin concentrations (Holtrop et al., 2016). However, while considerable effort is, quite understandably, expended to ensure shellfish safety, the impact of HABs on the economic sustainability of this regionally important industry remains unquantified. An economic assessment of the impact of HABs on the Scottish shellfish industry will therefore allow the financial assessment of alternative mitigation and management strategies for alleviating revenue losses in a HABs scenario.

There is an important literature on the valuation of harmful algal bloom (HAB) impacts in sectors like commercial and recreational fisheries, tourism and recreation and public health just to mention a few (Sanseverino et al., 2016; Groeneveld et al., 2018; Adams et al., 2018). The majority of these studies refer to physical and economic impacts observed in the US, with few studies from other regions (Adams et al., 2018). Studies of the economic impacts of HABs on aquaculture elsewhere are sparse, although Park et al. (2013) provide an example from Korea. Research on shellfish and finfish aquaculture in Europe is equally limited, with exceptions being the study of the impact of *Alexandrium* species on Galician (Spain) mussel farming, measured by correlating HAB incidence with industry metrics (Rodriguez et al., 2011). Ecological and economic consequences for the shellfish farming sector have been also addressed in Bourgneuf Bay (France) by an input-output (IO) analysis (Agundez et al., 2013).

A first attempt to provide analysis of the economic impact of HABs on several marine sectors in the US was made by Hoagland et al. (2002), with further research addressing more specifically the effect of HABs in sectors like commercial fisheries (Hoagland and Scatasta, 2006; Jin and Hoagland, 2008; Jin et al., 2008), recreational fisheries (Hoagland and Scatasta, 2006; Dyson and Huppert, 2010) and tourism (Hoagland and Scatasta, 2006; Taylor and Longo, 2010; Morgan et al., 2011). However, results of these studies are not necessarily comparable, because they are based on different and incommensurable metrics (Davidson et al., 2014). Some of them, for instance, measure direct impacts to the business and indirectly to the supply chain (by IO analysis), and are therefore not relevant for measuring benefits of policies through cost benefit analysis (for a list of recent studies implementing IO analysis, see Adams et al., 2018). Globally, studies make use of lost sales (gross revenues or turnover) (see Hoagland et al., 2002 for an example), while it is uncommon for the analysis of welfare measure such as consumer and producer surplus to be used as appropriate measures of cost of HAB to society[1]. Although lost revenues are commonly assumed as a

---

[1] Consumer surplus is the difference between the price that consumers are willing to pay (WTP) and the price they pay. Producer surplus is the difference between the price received by producers and the cost of production (the minimum willingness to accept - WTA).

proxy of economic welfare, this is true if the quantity of product that cannot be commercialized has been harvested and processed, but not sold. If the product is sold after the biotoxin levels subside, the gross revenue lost is overestimating the welfare lost by the producer. Furthermore, economic impacts are often based on a retrospective analysis of the average reduction in production following an algal bloom event, therefore implicitly inferring that reduction in production is exclusively caused by the HAB (this allows calculation of the average impact of the HAB on production) (Jin et al., 2008). Conversely, there is the need of an *ex ante* valuation of marginal expected damages caused by HABs, separating them from the impacts determined by other causes (e.g. changes in management and impacts of environmental-climatic variables), and to facilitate the comparison with the cost of measures reducing the risk from algal production.

An interesting approach that relates changes in environmental properties and damage to a marketed product is the dose response model, which measures the marginal damage in production caused by a specific environmental effect. The latter value can be simply multiplied by the unit price of the affected product to estimate the lost value (we are making the assumption that price does change after the environmental effect; this condition applies for relatively small changes in production). An example of a dose response model applied to HABs is provided by Jin et al. (2008) who assessed the impact of a red tide on commercial shellfish fisheries in Maine and Massachusetts. They compared revenues during the event and in previous years to estimate the average production change incurred. Then, to infer marginal impacts of the red tide on production, these authors performed a regression between production, dummies (categorical variables taking the value 0 or 1) for seasonal fluctuations, linear and quadratic time trends, and a dummy for red tide event. The same approach was used to address the effect of the red tide on price change and value of production.

Barbier (1998) and Hanley and Barbier (2009) showed a limitation of the dose response approach in that it ignores modification in the economic behavior of the individual affected by the environmental change. Hence, a better way to operationalize a damage function in the context of aquaculture is by the implementation of a production function approach, where the physical impact is one of the inputs in the function along with capital and labour. The marginal value of this impact is a measure of the physical change on the productivity of any marketed output (a monetary value can be obtained by multiplying this change by the market price). A dynamic version (i.e. considering time) of a production function approach was implemented in a bio-economic model by Fresard et al. (2006) to simulate the competition for space from an invasive species for the scallop fishery of the Bay of Saint-Brieuc (France), and then to quantify the net benefit of different scenarios simulating invasion control. The advantage of a dynamic approach is to take account of the effect on the stocks' reproduction rate that is ignored by the static approach. More commonly, studies implementing a static production function have been applied to agriculture to explore the marginal change in crop production of water recharge (Acharya and Barbier, 2000), but also to aquaculture to explore those inputs that affect productivity (amongst others stock density, fodder and fertilizer) (Asamoah et al., 2012). Static production functions have been used several times to explore the role of environment on fishery productivity by modelling the habitat-fishery linkage, as proposed by Lynne et al (1987), Ellis and Fisher (1987), Freeman (1991), Barbier (2000), Sathirathai and Barbier (2001) and Barbier et al. (2002). Conversely, there are no studies to our knowledge applying a production function approach to shellfish aquaculture affected by HABs.

This study proposes a static production function approach applied to aquaculture shellfish production in the four most productive Scottish shellfish harvesting regions (Shetland Islands, West Highlands, Outer Hebrides and Clyde) over the period 2009-2018, to estimate the impact of HABs and related biotoxins on shellfish industry productivity. The production function is preceded by a multivariate time series statistical approach (vector autoregression-VAR) to forecast the impact of biological and climatic variables on the production of biotoxins. Although the two models are independent, the VAR can be used to instrument biotoxins in the production function to forecast the expected impacts on shellfish production. Before moving to the details of the statistical approach and results, a brief description of the Scottish shellfish industry, along with the effects of climatic, environmental and biological factors on shellfish production is reported.

1.2 Shellfish production in West Scotland

Total shellfish production in West Scotland has been quite stable during the period 2009-2018 at an average of nearly 7,200 tonnes per year. The lowest production occurred in 2013 (6,935 tonnes), and the highest in 2016 (10,586). Over the same period, average price was £1,270/tonne (in real 2015 GBP). This production is carried out in nearly 160 active sites employing globally 330 workers. The region that exhibits the highest production is the Shetland Islands with 4,825 tonnes, followed by West Highlands (850 tonnes), Clyde (843 tonnes) and Outer Hebrides (678 tonnes). Shetland Islands is the region characterised by the highest capital-intensive production with 75 sites employing in total 112 staff.

Figure 1 provides a map of all the marine Scottish regions, but not the geolocation of the samples[2]. Our study refers only to the four highest shellfish producing regions, the Shetland Islands and the Western marine regions (Outer Hebrides, West Highlands, Argyll & Clyde).

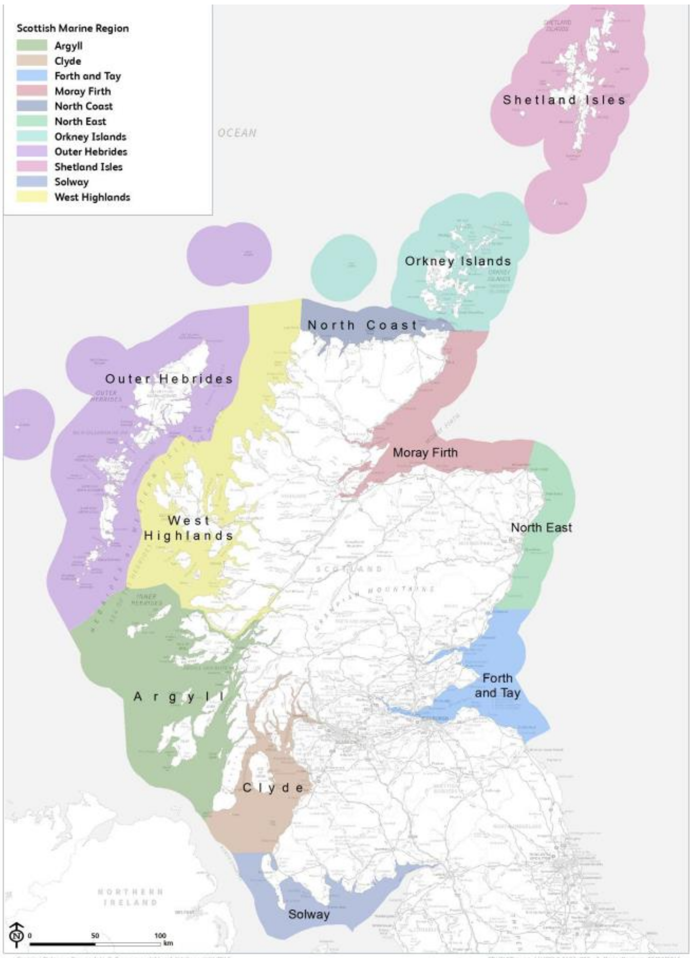

Figure 1: Map of the marine Scottish regions. Source: LUC, 2016

Within each region, biotoxins and HAB concentrations are evaluated (typically weekly) at a number of representative monitoring points (RMPs). Shellfish farms operate until biotoxin

---

[2] Marine Scotland reports the number of farms sampled in the annual publication “Scottish Shellfish production Survey”, available at the following web site: https://www.gov.scot/collections/scottish-fish-farm-production-surveys/. In 2019, 129 businesses where sampled, distributed as follows: 44 in the West Highlands, 5 in the Orkney Island, 23 in the Shetland Islands, 43 in the Clyde, and 14 in the Outer Hebrides. Consulted on 21st August 2020

concentrations at the relevant RMP exceed regulatory threshold (see Appendix Table A0) and all the farms associated with this RMP are then closed to harvesting. At concentrations close to the threshold, a risk management matrix that utilises phytoplankton and biotoxin data from the current and previous four weeks is used to determine the appropriate harvesting action. Mussels eventually depurate toxins naturally and reach health and safety conditions required by the market. However, because much of Scottish shellfish production fulfils commercial contracts to supply a particular quantity of product at a certain time, it is likely that this product will go out of phase with market demand and remain unsold.

1.3 Recent trends in climatic and environmental index, harmful algae and biotoxins

In many locations, the frequency and intensity of HAB events vary according to species and biotoxin both geographically and seasonally. Details on the spatial distribution of HABs in the Scottish marine regions are reported in Food Standards Scotland annual reports (e.g. Stubbs et al. 2015). Inter-annual variability is potentially related to climatological drivers (Belgrano et al., 1999; Moita et al., 2016; Wells et al. 2019). Nevertheless, higher occurrence of blooms during summer seasons suggests that increased sea surface temperature, light intensity and duration, and favourable wind conditions can enhance the proliferation of HABs (Chapelle et al., 2015; Cusack et al., 2016; Fraga et al., 1988; Peperzak, 2003; Whyte et al., 2014). Because of the complex fjordic nature of its coastline, spatial and temporal variability is a characteristic of Scottish waters with different HAB species blooming independently of each other (Davidson et al., 2016) as documented for *Dinophysis* (Swan et al., 2018), *Alexandrium* (Bresnan et al., 2008) and *Pseudo-nitzschia* (Roland-Pilgrim et al., 2019).

While Scottish HAB events are thought to be primarily influenced by environmental rather than anthropogenic factors (Gowen et al., 2012), the nature of this interaction, that differs for different species, remains a topic of active research (Bresnan et al., 2020). The North Atlantic Oscillation (NAO) varies between years (Fig. 2 right) without showing any trend. Advective transport of cells by oceanographic and wind driven currents, that are influenced by NAO, has been documented by a number of studies (e.g. Davidson et al., 2009, Whyte et al., 2014), but the mechanism of bloom initiation is less clear. Elevated NAO is related to the westerly winds that may advect harmful blooms developed offshore to the Scottish coastal aquaculture sites (Fehling et al., 2012, Aleynik et al., 2016, Whyte et al., 2014). Ocean warming (Fig. 2 left) has been associated with accelerating the growth rate and widening the distribution of toxic species such as *Dinophysis acuminata* and *Alexandrium fundyense* (Gobler et al., 2017; Wells et al., 2019) in Scottish waters, however other authors have been unable to verify such model predictions (Dees et al., 2017; Hinder et al., 2012).

The abundance of the diatom *Pseudo-nitzschia spp*. and its biotoxin product, domoic acid, were noted to increase with temperature by Rowland-Pilgrim et al. (2019), but also exhibiting high inter-annual variability. This genera and other diatoms have showed a positive relationship with the increasing trend of SST in the N.E. Atlantic and North sea using a 50 year time series of Continuous Plankton Recorder data (Hinder et al., 2012). In contrast the same authors showed a negative relationship between most dinoflagellates surveyed and SST.

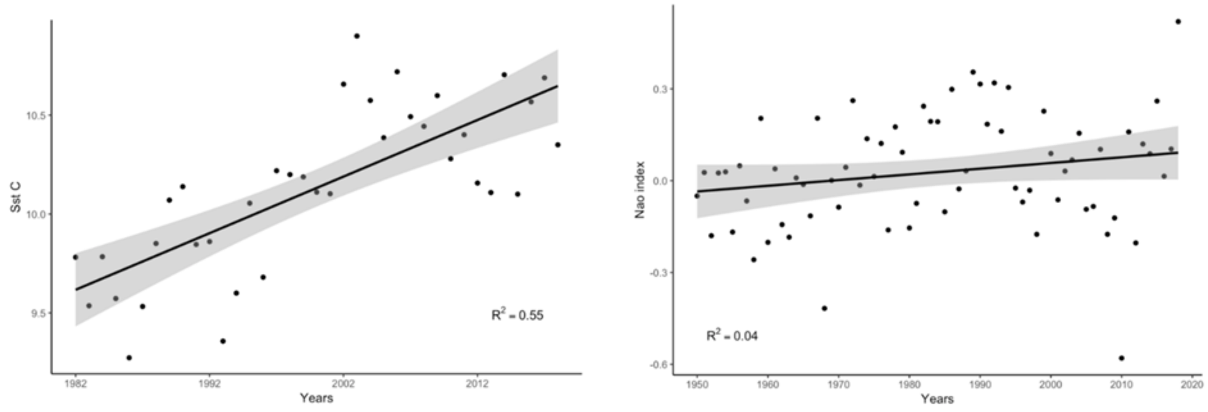

Figure 2: Left, SST yearly average for the time series 1982-2018, (PODAAC) website, carried out by NOAA. Right, Yearly NAO index 1950-2018, NOAA.

2. Data and Methods

2.1 Data

Our analysis is based on a panel built on the statistics reported by the "Scottish Shellfish Production Survey" (available years 2009-2018) (see: https://www.gov.scot/publications/)[3]. A panel is a database characterising different individuals or units observed at several points in time. For each region (unit) of Western Scotland where shellfish are produced (Clyde, West Highland, Outer Hebrides and the Shetland Islands), the panel is made of 10 (annual) observations (from 2009 to 2018).

---

[3] Digital data on shellfish production are provided by Marine Scotland. Data at: https://data.marine.gov.scot/dataset/scottish-shellfish-farm-production-survey-data.

Regional data used in the analysis are annual shellfish production (expressed in tonne - 96% are mussels), number of employees per region (labour), number of active production sites per region (a proxy for capital), and biological information on harmful algae and biotoxin concentration. Variables common to the four regions are climatological drivers such as sea surface temperature (SST) and the North Atlantic Oscillation (NAO). SST data were obtained from the Physical Oceanography Distributed Active Archive Center (PODAAC) website, reporting daily satellite (AVHRR) derived product with a spatial resolution of 0.25 degrees. The NAO index (interval -1 to 1) was obtained from daily values, calculated by the standard deviation of the monthly NAO index of the time series 1950-2000, by the NOAA National Weather Service Climate Prediction Centre.

Biological data are collected by weekly survey from April to October and fortnightly in winter from ~40 phytoplankton and ~80 biotoxin RMPs. These consist of the density of the different relevant HAB species/genera and their associated shellfish biotoxins. To address variability in sampling frequency in different locations these are averaged annually. Phytoplankton collection involves a 10-metre “Lund tube” or occasionally the use of a bucket at shallow water sites. The abundance of harmful phytoplankton cells is enumerated by light microscopy. Biotoxin levels in shellfish tissue are quantified analytically using liquid chromatography with tandem mass spectrometry (LC-MS/MS) and High Performance Liquid Chromatography (HPLC). These techniques were used from 2011, while in the previous years biological assays were employed. Common mussels represent 87% of the total shellfish samples and 62.3% of the samples within which biotoxin concentrations are above the safety threshold for consumption. This shellfish group was therefore chosen for our study since it is the dominant shellfish product in Scotland.

HAB abundance and biotoxin concentrations are characterised with respect to the regulatory threshold (Table A0 in Appendix). Abundance values taken from phytoplankton genera and concentrations of harmful shellfish biotoxins are classified in terms of the fraction of measurements (interval 0-1) above the regulatory safety threshold. For phytoplankton, the regulatory threshold is determined by the United Kingdom National Reference Laboratory for marine biotoxins (UKNRL). For biotoxins, this threshold is provided by the regulation (EC) No 853/2004 of the European parliament (European Union, 2004).

2.2 Methods

2.2.1 The vector autoregression model

It is possible to forecast the variation in shellfish production if we have a dynamic model describing the expected concentration of biotoxins and HABs (see Davidson et al., 2016 and references therein). A simple approach to forecast biotoxins is a multivariate time series model in which each variable is regressed versus lagged regressors, including the dependent variable (vector autoregression - VAR). This is a stochastic process capturing the linear interdependencies among time series. In a VAR, each variable has an equation explaining its evolution based on its own lagged values, the lagged values of the other model variables, and an error term (Verbeek, 2017). The VAR model proposed here does not mimic the physical relations between biotoxins and climatic variables, but describes how variables affect each other inter-temporally. The optimal order of the lagged variable, usually selected by BIC and AIC criterion (Verbeek, 2017), is indicated by the letter “p”. A VAR is usually explained by the following matrix expression:

$$Yt = c + A1Y(t-1) + A2Y(t-2) + \cdots + ApY(t-p) + et \qquad \text{Eq.1}$$

where *Yt* is the vector of dependent variables at the current time t, the observation *Y(t-i)* up to the order *p* is the *i-th* lag of vector *Y*, *c* is a vector of constants (intercepts), *A1, A2,…,Ap are* time-invariant matrices of coefficients at lag 1,2,…p, and et is a k-vector of error terms with zero mean and no serial correlation. In a VAR, all the variables must be stationary, i.e. mean variance, autocorrelation, etc. are all constant over time. Stationarity of vector *Yt* is verified for our data set according to the augmented Dickey-Fuller test (Dickey and Fuller, 1979) as reported in the Appendix Table A1.

2.2.2 The Cobb-Douglas production function

A production function is a mathematical relation that defines the highest level of production achievable as a function of a range of inputs, such as labour and capital (Cobb and Douglas, 1928). Alternative models including environmental variables as input factors are common for the agriculture sector (Umar et al., 2017). Eq.2 depicts the relationships between shellfish production and several covariates, including climatic variables (SST and NAO) and ecological information (the concentration of harmful algae and biotoxins).

$$Productionjt = Aj * Kjt^{\beta 1} * Ljt^{\beta 2} * e^{\beta 3SSTt + \beta 4NAOt + \beta 5HABjt + \beta 6BTXjt} * \varepsilon jt \qquad \text{Eq.2}$$

where *Production* is shellfish production (allocated to market) in tonnes, *K* is capital, proxied by the number of active producing sites, *L* is labour, the total number of employees; *SST* and *NAO* are the sea surface temperature in degrees Celsius, and the North Atlantic climatic index (in the range -1 to 1), respectively; *j* is an index for the j^{th} region (unit) of production at time t. *HAB* is the vector of harmful algal bloom variables, and *BTX* is a vector of biotoxin variables produced by the *HAB*. Both are expressed in frequency, i.e. the fraction (interval 0-1) of algal cell and biotoxin concentration above a harmful threshold that impedes the commercialisation of shellfish (reported in Table A0 of the Appendix). The symbol e is the mathematical constant (Euler's number) approximately equal to 2.71828, the base of the natural logarithm[4]. Finally, *A* is the constant that refers to technology or management producing strategies and ε is the error term. Hence, A is the amount of production for a unit value of *K* and *L,* while the effect of *SST, NAO*, *HAB* and *BTX* is null. The beta coefficients of Eq.2 measure the impact of each covariate on shellfish production. To estimate Eq.2, all variables with the exclusion of *SST, NAO*, *HAB* and *BTX*, are transformed in natural log. Eq. 2 then becomes:

$$lnProductionjt = LnAj + \beta1lnKjt + \beta2lnLjt + \beta3SSTjt + \beta4NAOjt + \beta5HABjt + \beta6BTXjt + ln\varepsilon\text{jt} \qquad \text{Eq.3}$$

Having operated this transformation, the beta coefficients of *K* and *L* ($\beta1$ and $\beta2$, respectively) can be interpreted as elasticities, i.e. the percentage variation in production triggered by a percentage change in capital and labour. As *HAB* and *BTX* are measured as frequency (0 to 1), the interpretation of their respective beta coefficients is that 1% change in *HAB* and *BTX* causes a relative change in production nearly equivalent to the beta coefficient. The constant *lnA* refers to the natural log of production under unitary labour and capital. The HAB and BTX beta coefficients can then be seen as the marginal change of productivity under undesirable conditions.

---

[4] It is necessary to introduce in the Cobb-Douglas the exponential of SST, NAO, HAB and BTX because under this formulation there is no adverse effect on production of shellfish if these variables are equal to zero. Conversely, a multiplicative formulation would imply zero production under a null value of one of these environmental variables (the latter formulation is obviously incorrect).

In Eq.3 climatic variables and HAB have a mediating, but not direct, effect on shellfish production through their influence on BTX (see Supplementary Material 1 for more information). Thus BTX are endogenous variables (i.e. that are influenced by other variables, and then generated within the model), while SST, NAO and HAB are exogenous variables (whose value is determined outside the model). To treat this issue, we solved Eq.3 by a regression with instrumental variables, where the instruments are the exogenous variables SST, NAO and HAB correlated to the instrumented or endogenous variable (BTX), but uncorrelated with the error terms of Eq.3 and unaffected by the remaining variables.

A panel data regression with instrumental variables is executed in two stages: the first is a regression between the endogenous variable and exogenous regressors to test for the goodness of the instrument (weak correlations can lead to misleading estimates for parameters and standard errors of Eq.3). The second regression is the analysis of the panel where the instrumented variable is replaced by the predicted values of the first stage regression. For details, see Verbeek (2017). To take account of this endogeneity, Eq.3 is therefore simplified as follows:

$$lnProductionjt = LnAj + \beta 1 lnKjt + \beta 2 lnLjt + \beta 6 BTXjt + ln\varepsilon jt \qquad \text{Eq.4}$$

where labour and capital are exogenous and BTX is instrumented by NAO, SST and HABs.

Eq.4 is estimated using both fixed and random effect estimator to depict the impacts of BTX on shellfish production. A fixed effect estimator provides meaningful results explaining the differences between units (the productive regions). Such estimator assists in controlling for unobserved heterogeneity when this heterogeneity is constant over time and correlated with the independent variables. This heterogeneity is usually removed from the data by regressing the mean-corrected variables (i.e. the difference of each observation from the variable’s mean). We can assume that in the production function time invariant omitted variables can be management practices (different strategies that are adopted in production, for example to mitigate the impacts of algal blooms that are not observed and captured by the model) and the site characteristics of the farm such as the particular habitat or substrate. Under the fixed effect estimator, we assume that each unit or region has its own specific characteristics (modelled by a unique intercept) rather than being considered a random draw from the same population. These unit-specific means (*lnAj* in Eq.4) take account of the regional variability in the productivity of each region. The two stage least squares (2SLS) estimator with regional dummy variables is used to capture the productivity of each unit. Conversely, the random effect model does not estimate any fixed time invariant intercept for each unit, but assumes that the regions are drawn from a larger (random) sample. This model assumes also that unobserved heterogeneity is not correlated with the independent variables. The random effect coefficients are estimated by the two stages generalised least squares estimator (G2LS). Statistical analysis was carried out in STATA version 16.0.

3. Results

3.1 Descriptive statistics

Table 1A, 1B, 1C summarise the average values for all the covariates for each unit of the panel. A large difference is discernible between the Shetland Islands and the other regions. In particular, the production in Shetland is at least twice as high as in all other regions and is achieved by employing the lowest number of workers per site (Table 1A). It is therefore evident that Shetland has the lowest labour intensity measured as labour to capital ratio (1.48 labour units per active site compared to 2 to 3 labour units per site of the other regions) (Table 1A). As regards algal concentration, only the genera *Alexandrium, Dinophysis and Pseudo-nitzschia* overcome significantly the harmful threshold (see Table 1B), while amongst the biotoxins, those causing DSP most frequently exceed regulatory threshold (Table 1C).

Table 1A, 1B, 1C here

Table 2 reports the pairwise correlation between all the variables. Significant correlations are denoted with an asterisk. Production is positively related to capital and labour as expected, but capital and labour are highly correlated suggesting potential collinearity. Positive changes in the climatic index NAO, associated with offshore-onshore advection of cells, is expected to increase the concentrations of DSP biotoxins. SST has an inverse impact on PSP, but does not affect any other biological variables. Finally, *Pseudo-nitzschia* is negatively related to DSP, PSP and AZP, consistent with the observation that environmental conditions that facilitate the proliferation of diatoms do not favour the growth of dinoflagellates.

Table 2 here

3.2 Prediction of DSP biotoxins: the VAR model

Table 3 shows the statistical relations between climatic index, HAB and BTX variables (as provisionally depicted by the pairwise correlation shown in Table 2) to forecast concentration of biotoxins at time *t* having information of all covariates at time *t-1* (at higher lags, no significant result is found). Only the regression presenting DSP as dependent variable is reported, because of the highest explained variance (R squared 67%) and the importance of DSP in affecting production in the Cobb-Douglas model presented in section 3.3.

Table 3 here

It is evident from the coefficients reported in Table 3 that lagged values of DSP do not explain the current value of DSP (i.e. blooms in a particular year are independent of those in previous years). As expected, *Dinophysis spp*., that is the main causative dinoflagellates of toxins generating DSP in Scotland (Swan et al., 2018), is positively contributing to DSP. Conversely, *P. lima,* that can also generate DSP toxins, is negatively related. This opposite response is not however a surprise: *Dinophysis spp*. and *P. lima* have different life cycles, so there is no expectation that both will bloom at the same time. Finally, the NAO index is highly correlated at lag 1 with DSP. In other words, we can say that data lagged 1 year for NAO are able to forecast the current (present) DSP. This relationship is positive; this means that a higher NAO index contributes to increase the concentration of DSP biotoxins. The result is not easily interpretable from an ecologically perspective, especially for the low temporal resolution of the database and because this regression does not mimic any structural behaviour in DSP formation, i.e. it is not clear ecologically how NAO the previous year influences DSP in the current year. However, the predictive capacity of a VAR is quite good and can contribute to forecast DSP, in the absence of a complex physical model working at higher spatial and temporal resolution. Although this result is *per se* meaningful, it can also be used with the regression model described in section 3.3 to predict the expected damage on shellfish production and facilitate mitigating losses in production with an ample temporal margin. To achieve this, the predicted value of DSP from the VAR can be multiplied by the marginal change in production caused by DSP (section 3.3). An estimate of average damage caused by the value of DSP in the period 2009-2018 is reported in the discussion.

3.3 The econometric model

Supplementary Material 1 reports several tests justifying the choice of a panel data regression with instrumental variables to estimate Eq.4. Table 4a reports the coefficients estimated by the random effect estimator, while Table 5a reports results from the fixed effect estimator, the latter to take account of the potential differences in productivity between regions, as evidenced by Table 1. Estimates are accompanied by clustered robust standard errors to correct for the presence of heteroscedasticity (Supplementary Material 2 plots residuals versus fitted values showing non-homogeneous dispersion of residuals).

Table 4b and Table 5b report the first stage regression under random and fixed effect estimators respectively, showing the goodness of the instrumental variables in predicting DSP. All covariates included in the models proposed are statistically significant.

The random effect estimator shows that labour is negatively related to production, a result that is economically counterintuitive. Conversely, as expected, the effect of capital on production is positive and elastic, showing that 1% increase in capital contributes to increase production by 1.88%. The marginal effect of DSP on production is close to 1, meaning that 1% increase in DSP causes nearly 1% reduction in production.

Table 4a here (random effect)

Table 4b here (first stage random effect)

Under the fixed effect model, labour does not show any statistically significant effect on productivity. This can be interpreted as the possibility that farming has reached the highest level of productivity given the capital employed (according to the law of marginal diminishing return), i.e. one unit more of labour does not contribute to an increase in productivity[5]. Conversely, the impact of capital is positive and close to the unit elasticity. The impact of DSP is -0.66, i.e. 1% increase in DSP causes a reduction of 0.66% in shellfish production. The constant term shows the productivity for the Clyde region. The coefficient for the Outer Hebrides, West Highlands and Shetland Islands shows the additional productivity above that of the Clyde region[6]. Table 5a coefficients for the regions Outer

---

[5] Removing from the panel data regarding the Shetlands Island, the region characterized by the highest intensity of capital, both labour and capital become insignificant. This shows that results from labour is in part due to the limited variability of the database, while that from capital is influenced by the higher productivity of Shetland's farms.

[6] By adding the constant (coefficient for the Clyde) to the specific coefficient of the region of interest, it is possible to obtain the fixed term effect for any region. The coefficient of the Outer Hebrides is therefore 4.265 (standard error of 1.635); that of West Highlands is 4.226 (standard error 1.973), while Shetland is 5.068 (standard error 2.244), confirming the highest productivity in this region as expected from descriptive statistics in Table 1.

Hebrides and West Highlands do not show any significant incremental productivity compared to the Clyde, while Shetland Islands show a significant higher productivity as expected from Table 1. The null hypothesis on the equality of the coefficients between the Clyde and Outer Hebrides (chi2(1)=0.16, prob>chi2=0.689) and Clyde and West Highlands (chi2(1)=0.54, prob>chi2=0.462) cannot be rejected, while a significant difference exists between Clyde and the Shetlands (chi2(1)=42.91, prob>chi2=0.000), confirming the highest productivity of the second region as expected from descriptive statistics in Table 1.

Table 5a here (fixed effect)

Table 5b here (first stage fixed effect)

To estimate the impact of DSP on shellfish production we opted for the coefficients provided by the fixed effect model. This has the advantage of considering difference in productivity among sites (the different regions appears as single independent units) and removing time invariant aspects related to the management of the fisheries. This model also provides a lower marginal impact of DSP on production compared to the random effect model. Finally, the Hausman test (Verbeek, 2017) confirms fixed effect to be the most efficient estimator (chi2(3) = 41.88, Prob>chi2 = 0.0000).

4. Discussions and conclusions

4.1 Main findings and implications for shellfish management

We have investigated the extent to which shellfish production in Scotland is influenced by algal toxins proposing two models: a VAR to depict the relation between biological, climatic drivers and biotoxins concentration and a production function to describe the impact of biotoxins on shellfish production. The VAR found a statistically significant relationship between a positive change in some harmful algae, the NAO index and DSP biotoxins. This result is interesting because environmental drivers of A*lexandrium, Dinophysis* and *Pseudo-nitzschia* blooms (Smayda, 2004, Davidson et al., 2011, Bresnan et al., 2020) have not been clearly explained (Dees et al., 2017, Bresnan et al., 2020). Future development of the VAR at higher resolution may capture the ecology of DSP formation. For example, findings of this model can be further investigated to check if they are consistent with the hypothesis that Scottish DSP events are related to changes in atmospheric pressure and hence that *Dinophysis* blooms develop offshore and are advected to the coast (Whyte et al., 2014; Aleynik et al., 2016, Paterson et al., 2017).

The production function showed that DSP toxicity on production follow a non-linear pattern, i.e. shellfish production changes at decreasing rate (speed of change) at higher concentration of DSP biotoxins. In particular, we found that a 1% change in DSP biotoxins above the harmful threshold defined for regulatory purposes causes a reduction in production of 0.66%. Considering that the average yearly proportion of DSP biotoxin concentration above the threshold in the last 10 years has been 24% (see Table 1), these toxins are expected to cause a yearly average reduction of nearly 15% in production (95% confidence interval -20% to -10%). This change is equivalent to a loss of 1,080 ton of shellfish per year (95% confidence interval -1,490 ton to -670 ton). At the average price of £ 1,272 per ton (in 2015 constant GBP), the average annual economic damage (expressed as lost gross revenue) caused by DSP is equivalent to £ 1.37m (95% confidence interval £-1.9m to £-0.85m) over a turnover of approximately £10.1m.

Other authors (Hoagland et al. 2002) used as an indicator of economic impact the lost revenue. Under the assumption that harvested production cannot be easily commercialised after the ban, as it happens for the Scottish shellfish, lost revenue becomes a good indicator of the real benefits lost (producer surplus).

Commonalities with case studies reported in the literature are difficult to find because of the paucity of research applied to shellfish production and inconsistency in the methodologies used to assess impacts. HAB damage to Korean shellfish aquaculture over the past 3 decades amounted to US$ 4m per year and peaked in 1995 to US$ 60m, almost a 10% loss of all cultured shellfish produced that year (Park et al., 2013). In percentage terms, this figure is similar to our findings. In another study carried out in Spain (Rodriguez et al., 2011), the economic impact of DSP biotoxins on mussel production was not yet clearly established. A difficulty in forecasting the economic loss caused by DSP in the Spanish market is related to the possibility to sell part of the produce after shellfish depurate. In fact, while significant biotoxin events may lead to a reduced harvest, the Spanish case demonstrates that at least part of the production that cannot be harvested during the closure of the fishery can be marketed after the prohibition period (Rodriguez et al., 2011). This is not always possible in Scotland, although mitigating measures do exist such as shifting production to adjacent sites, if possible. Some cooperatives (for example the Scottish Shellfish Marketing Group) help farmers in different geographical areas to work together to switch production to fjords that have not been impacted by HABs.

The mitigating strategies mentioned above can be adopted by firms to adapt capital and labour to maximise production in light of environmental conditions. The Cobb-Douglas approach, as it considers capital as input factor, is able to include more explicitly farmers behavioural as captured by the varying number of sites of production in order to anticipate production during a HAB event. This cannot be modelled in the dose response model (Jin et al., 2008; Rodriguez et al., 2011).

In terms of management implications for the Scottish shellfish industry, results from the production function show that shellfish production is more efficient in the Shetland Islands, characterised by higher productivity compared to the regions of the west coast. These results offer insight into regional differences in operation and the environmental characteristics of the sites. Although not an object of this study, we can say that studying the productivity in the different regions would allow more informed management to support the sustainable development of the shellfish industry. In the West Highlands, characterized by a lower productivity, the impact on production is marginally more damaging than in the Shetlands, suggesting managers may be able to put in place strategies to minimize the impacts of harmful algae, from shifting production sites to rearranging contractual agreements with wholesalers and retailers.

4.2 *Limits of the model*

There are some limits to our econometric model that future research should address. The first one is the lack of suitable variables to explain capital and labour in the West Highland farms that both show a limited variability in the period 2009-2018. In addition, the capital of the fishery shows a high correlation with labour (Table 1), and may be the cause of the non-significance of the variable labour in the regression. We found that the ratio of workers to active sites is approximately constant over time with a value of ~two. A constant labour to capital ratio is typical of a production function characterised by a relation of complementarity between capital and labour (i.e. production is achieved using the same units of capital and labour), while the Cobb-Douglas production function is characterised by capturing the substitutability between factors (production can be achieved trading-offs capital against labour or vice versa). Therefore, further development of the model requires a different proxy for the capital: this can be the area that each farm is dedicating to production, the number of producing longlines, or the ratio between longlines and area. These data were not available to us for this study, but could potentially be collected by questionnaire survey at farm level.

While the HAB and biotoxin time series available to us are possibly unique in length, both in temporal and spatial resolution, our analysis is also limited by the lower resolution of, for example, production data, which is surveyed only annually. The regression model proposed simulates the impacts of HAB and biotoxins concentration over the regulatory safety threshold and on averaged yearly production. Thus, this approach is able to capture the variability of biotoxins which are characterised by medium term blooms lasting for much of a season as can be the case for *Dinophysis spp*, which occur anywhere on Scottish coastal waters without a clear and evident regional pattern (Smayda, 2004, Coates et al., 2018, Bresnan et al., 2020,), and therefore are likely to have a non-seasonal impact on shellfish harvesting. Conversely, short term blooms of PSP toxins from the genus *Alexandrium,* which are regularly detected in mussels during the summer months (Bresnan et al., 2008), are not captured by our model because of its limited temporal resolution (1 year). Hence, we are unable to capture factors such as seasonality of HAB and its impact on shellfish productivity. Ideally, future studies would include higher temporal resolution farm data (possibly by capturing seasonal production at farm scale by questionnaire survey of all farms). This would have the advantage of distinguishing whether each site differs from others and if seasonal HAB events have an impact on production. Availability of data at a higher temporal resolution would also facilitate the implementation of a more general function such as the translog that is able to capture non-linear (quadratic) and cross-effects among the regressors (Umar et al., 2017), and may reveal more detailed temporal or spatial impacts of HABs on production.

A final consideration is how to get the best from the results of this model. These could be maximised in future research by a model capturing the dynamics of the shellfish market, to provide insights on the equilibrium between demand and supply and to address HABs impacts not only on the shellfish harvest, but also on prices to allow estimation of welfare changes from the side of consumers.

Acknowledgement

We thank PICES for travel support to attend the GlobalHAB HABs/Economics workshop at the 2019 PICES annual science meeting. KD was funded by the UK RCUK projects OFF-AQUA and CAMPUS and the EU Atlantic Area Interreg project PRIMROSE. FG was funded by an Ocean Risk Studentship from AXA-XL.

References

Acharya, G., Barbier, E.B., 2000. Valuing groundwater recharge through agricultural production in the Hadejia-Jama’are wetland in Northern Nigeria. Agr Econ, 247-59.

Adams, C.M., Larkin, S., L., Hoagland, P., Sancewich, B., 2018. Assessing the economic consequences of harmful algal blooms: a summary of existing literature, research methods, data and information gaps. In Harmful Algal Blooms: A Compendium Desk Reference, Shumway S.E. Burkholder J.A.M, Morton S.L. (eds), pages 337-354. John Wiley & Sons Ltd.

Agundez, J.P., Raux, P., Girard, S., Mongruel, R., 2013. Technological adaption to harmful algal blooms: socioeconomic consequences for the shellfish farming sectors in Bourgeuf Bay (France). Aquacult Econ Manag 17, 341–359.

Aleynik, D., Dale, A.C., Porter, M., Davidson, K. 2016. A high resolution hydrodynamic model system suitable for novel harmful algal bloom modelling in areas of complex coastline and topography. Harmful Algae 53, 102-117.

Asamoah, E.K., Nunoo, F.K.E., Asare, Y.B., Addo S., Sumaila, U.R., 2012. A production function analysis of pond aquaculture in southern Ghana. Aquacult Econ Manag 16(3), 183-201.

Barbier E.B., 2007. Valuing ecosystem services as productive inputs. Econ Policy 22(49), 179-229.

Barbier, E.B., 1998. The economics of soil erosion: theory, methodology, and examples. Chapter 13, in E.B. Barbier (eds), The economics of Environment and Development: Selected Essays, Cheltenham, UK and Northampton, MA, USA. Edward Elgar, pp 281-307.

Barbier, E.B., 2000. Valuing the environment as input: application to mangrove-fishery linkages. Ecol Econ 35, 7-61.

Barbier, E.B., Strand, I., 1998. Valuing mangrove-fishery linkages: a case study of Campeche, Mexico. Environ Resour Econ 12, 151-166.

Barbier, E.B., Strand, I., Sathirathai, S., 2002. Do open access conditions affect the valuation of an externality? Estimating the welfare effects of mangrove-fishery linkages. Environ Resour Econ 21(4), 343-367.

Belgrano A, Lindahl O, Hernroth B., 1999. North Atlantic Oscillation primary productivity and toxic phytoplankton in the Gullmar Fjord, Sweden (1985-1996). Proc R Soc B Biol Sci. 266 (1418), 425–30.

Berdalet, E., Fleming, L.E., Gowen, R., Davidson, K., Hess, P., Backer, L.C., Moore, S.K., Hoagland, P., Enevoldsen, H., 2016. Marine harmful algal blooms, human health and wellbeing: challenges and opportunities in the 21st century. J Mar Biol Ass UK 96:61-91.

Bresnan, E., Baker-Austin, C., Campos, C.J.A., Davidson, K., Edwards, M., Hall, A., McKinney, A., Turner, A.D., 2020. Impacts of climate change on human health, HABs and bathing waters, relevant to the coastal and marine environment around the UK. MCCIP Science Review, 521-545 http://www.mccip.org.uk/media/2025/22_human_health_harmful_species_2020.pdf

Bresnan, E. Turrell, E., Fraser, S., 2008. Monitoring PSP and *Alexandrium* hotspots in Scottish waters. In Proceedings of the 12th International Conference on Harmful Algae (Moestrup, Ø., Doucette, G., Enevoldson, H., Godhe, A., Hallegraeff, G., Luckas, B., Lundholm, N., Lewis, J., Rengefors, K., Sellner, K., Steidinger, K., Tester, P., Zingone, A., editors), 76–79. Intergovernmental Oceanographic Commission of UNESCO.

Chapelle, A., Le Gac, M., Labry, C., Siano, R., Quere, J., Caradec, F., 2015. The Bay of Brest (France), a new risky site for toxic *Alexandrium minutum* blooms and PSP shellfish contamination. Harmful Algae News 51, 4–5.

Coates, L., Swan, S., Davidson, K., Turner, A., Maskrey, B., Algoet, M. 2018. Annual report on the results of the biotoxin and phytoplankton official control monitoring programmes for Scotland - 2017. Available at: https://www.cefas.co.uk/media/201471/c-users-ocm00-desktop-del-2017-scotland-biotoxin-phytoplankton-official-control-monitoring-annual-report.pdf

Cusack, C., Dabrowski, T., Lyons, K., Berry, A., Westbrook, G., Salas, R., et al., 2016. Harmful algal bloom forecast system for SW Ireland. Part II: Are operational oceanographic models useful in a HAB warning system. Harmful Algae 53, 86–101. Available from: http://dx.doi.org/10.1016/j.hal.2015.11.013

Davidson, K., Bresnan, E., 2009. Shellfish toxicity in UK waters: a threat to human health? Environ Health 8 (Suppl 1), S12 doi:10.1186/1476-069X-8-S1-S12

Davidson, K., Miller, P.I., Wilding, T., Shutler, J., Bresnan, E., Kennington, K., Swan, S. 2009. A large and prolonged bloom of *Karenia mikimotoi* in Scottish waters in 2006. Harmful Algae 8, 349-361.

Davidson, K., Tett, P., Gowen, R.J., 2011. Harmful Algal Blooms. In: Marine Pollution & Human Health (Eds Harrison R. and Hester R.) Issues in Environmental Science and Technology. RSC publishing. pp 95-127. ISBN 978-1-84973-240-6

Davidson, K., Gowen, R.J., Harrison, P.J., Fleming, L., Hoagland, P., Moschonas, G., 2014. Anthropogenic nutrients and harmful algae in coastal waters. J Environ Manage 146, 206-216.

Davidson, K., Anderson, D.M., Mateus, M., Reguera, B., Silke, J., Sourisseau, M., Maguire, J., 2016. Forecasting the risk of harmful algal blooms: preface to the Asimuth special issue. Harmful Algae 53, 1-7.

Dees, P., Bresnan, E., Dale, A., Edwards, M., Johns, D., Mouat, B., Whyte, C., Davidson, K. 2017. Harmful algal blooms in the Eastern North Atlantic Ocean. Proceedings of the National Academy of Sciences 114 (46) E9763-E9764; www.pnas.org/cgi/doi/10.1073/pnas.1715499114

Dickey, D. A., Fuller, W. A. 1979. Distribution of the Estimators for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association 74 (366), 427–431.

Dyson, K., Huppert, D.D., 2010. Regional economic impacts of razor clam beach closures due to harmful algal blooms (HABs) on the Pacific coast of Washington. Harmful Algae 9, 264–271. https://doi.org/10.1016/j.hal.2009.11.003.

Ellis, G.M., Fisher, A.C., 1987. Valuing the environment as input. J Environ Manage 25, 149-56.

European Union, 2004. Regulation (EC) No 853/2004 of the European Parliament and of the council Off J Eur Union 2002, L139/55

European Union, 2019. The EU fish market. Publication Office of the European Union, Luxembourg, 102 pp doi:10.2771/168390

Fehling, J., Davidson, K., Bolch, C.J., Brand, T., Narayanaswamy, B.E., 2012. The Relationship between Phytoplankton Distribution and Water Column Characteristics in North West European Shelf Sea Waters. PLoS ONE 7(3), e34098.

Fraga, S., Anderson, D.M., Bravo, I., Reguera, B., Steidinger, K.A., Yentsch, C.M., 1988. Influence of upwelling relaxation on dinoflagellates and shellfish toxicity in Ria de Vigo, Spain. Estuar Coast Shelf Sci 27, 349–61. Available from: https://www.sciencedirect.com/science/article/pii/0272771488900935

Freeman III, A.M., 1991. Valuing environmental resources under alternative management regimes. Ecol Econ 3, 247-256.

Fresard, M., Boncoeur, J., 2006. Controlling the biological invasion of a commercial fishery by a space competitor: a bioeconomic model with reference to the bay of St-Brieuc scallop fishery. Agric Resour Econ Rev. 35 (1), 78-97.

Gobler, C.J., Doherty, O.M., Hattenrath-Lehmann, T.K., Griffith, A.W., Kang, Y., Litaker, R.W., 2017. Ocean warming since 1982 has expanded the niche of toxic algal blooms in the North Atlantic and North Pacific oceans. Proc Natl Acad Sci U. S. A. 114 (19), 4975–4980.

Gowen, R.J., Tett, P., Bresnan, E., Davidson, K., McKinney, A., Milligan, S., Mills, D.K., Silke, J., Gordon, A., Crooks, A.M., 2012. Anthropogenic Nutrient Enrichment and Blooms of Harmful Micro-algae. Oceanography and Marine Biology: An annual review 50, 65-126.

Groeneveld, R.A., Bartelings, H., Borger, T., Bosello, F., Buisman, E., Delpiazzo, E., Eboli, F., Fernandes, J.A., Hamon, K.G., Hattam, C., Loureiro, M., Nunes, P.A.L.D., Piwowarczy, J. Schasfoort, F.E., Simons, S.L., Walker, A.N. 2018. Economic impacts of marine ecological change: Review and recent contributions of the VECTORS project on European marine waters. Estuar Coast Mar Sci 201, 152-163.

Hanley, N., Barbier, E.B., 2009. Pricing Nature. Cost benefit analysis of Environmental Policy Edward Elgar Cheltenham, UK and Northampton, MA, USA.

Highlands and Islands Enterprise, Marine Scotland. 2017. The Value of Aquaculture to Scotland. 130pp

Hoagland, P., Anderson, D.M., Kaoru, Y., White W., 2002. The economic effects of harmful algal blooms in the United States: estimates, assessment issues and information needs. Estuaries 25(4b), 819-837.

Hoagland, P., Scatasta, S., 2006. The Economic Effects of Harmful Algal Blooms, in: Granéli, E., Turner, J.T. (Eds.), Ecology of Harmful Algae, Ecological Studies. Springer, Berlin, Heidelberg, pp. 391–402. https://doi.org/10.1007/978-3-540-32210-8_30.

Holtrop, G., Swan, S., Duff, B., Wilding, T., Narayanaswamy, B., Davidson, K., 2016. Risk assessment of the Scottish monitoring programme for the marine biotoxins in shellfish harvested from classified production areas: review of the current sampling scheme to develop an improved programme based on evidence of risk. FSS/2015/021. 218pp. https://www.foodstandards.gov.scot/downloads/Risk_assessment_of_the_Scottish_monitoring_programme_for_the_marine_biotoxins_1.pdf

Jin, D., Hoagland, P., 2008. The value of harmful algal bloom predictions to the nearshore commercial shellfish fishery in the Gulf of Maine. Harmful Algae 7, 772–781. https://doi.org/10.1016/j.hal.2008.03.002

Jin, Di, Thunberg, E., Hoagland, P. 2008. Economic impact of the 2005 red tide event on commercial shellfish fisheries in New England. Ocean Coast Manage 51, 420-429.

Knowler, D., 2005. Reassessing the costs of biological invasion: *Mnemiopsis leidyi* in the Black sea. Ecol Econ 52(2), 187-199.

Lynne, G.D.P., Conriy, P., Prochaska, F.J., 1981. Economic value of marsh areas for marine production process. J Environ Econ Manage 8, 175-186.

LUC, 2016. Scottish marine recreation and tourism survey 2015.

McKinney, A., Milligan, S., Mills, D.K., Silke, J., Gordon, A., Crooks, A.M., 2012. Anthropogenic Nutrient Enrichment and Blooms of Harmful Micro-algae. Oceanography and Marine Biology: An annual review 50, 65-126.

Moita, M.T., Pazos, Y., Rocha, C., Nolasco, R., Oliveira, P.B., 2016. Toward predicting Dinophysis blooms off NW Iberia: A decade of events. Harmful Algae 53, 17–32. Available from: http://dx.doi.org/10.1016/j.hal.2015.12.002

Morgan, K.L., Larkin, S.L., Adams, C.M., 2011. Empirical analysis of media versus environmental impacts on park attendance. Tourism Manage 32, 852–859. https://doi.org/10.1016/j.tourman.2010.07.010.

MSS, 2018. Marine Scotland Science, Scottish Shellfish Farm Production Survey 2018 https://www.gov.scot/publications/scottish-shellfish-farm-production-survey-2018/

Munro, LA., Wallace, I.S., 2018. Marine Scotland Science Scottish Shellfish Farm Production Survey 2017 Report. 31pp

Newell, C.R., S.E. Shumway, Cucci, T.L., Selvin, R., 1989. The effects of natural seston particle size and type on feeding rates, feeding selectivity and food resource availability for the mussel, *Mytilus edulis* Linnaeus, 1758 at bottom culture sites in Maine. J Shellfish Res 8, 187-196.

Park, T.G., Lim, W.A., Park, Y.T., Lee, C.K., Jeong, H.J., 2013. Economic impact, management and mitigation of red tides in Korea. Harmful Algae 30 (1), S131eS143.

Paterson, R.F., McNeill, S., Mitchell, E., Adams, T., Swan, S.C., Clarke, D., Miller, P.T., Bresnan, E., Davidson, K., 2017. Environmental control of harmful dinoflagellates and diatoms in a fjordic system. Harmful Algae 69, 1-17

Peperzak, L., 2003. Climate change and harmful algal blooms in the North Sea. Acta Oecol 24, 139–44.

Rodriguez, G.R., Villasante, S., Garcia Negro M.C., 2011. Are red tides affecting economically the commercialization of the Galician (NW Spain) mussel farming? Mar Policy 35, 52–257.

Rowland-Pilgrim, S., Swan, S.C., O'Neill, A., Johnson, S., Coates, L., Stubbs, P., Dean, K., Harrison, K., Teixeira, A.M., Walton, A., Davidson, K., Turner, A.D., Maskrey, B.H., 2019. Variability of Amnesic Shellfish Toxin and *Pseudo-nitzschia* occurrence in bivalve molluscs and water samples – analysis of ten years of the official control monitoring programme. Harmful Algae 87 101623 https://doi.org/10.1016/j.hal.2019.101623

Sanseverino, I., Conduto, D., Pozzoli, L., Dobricic S., Lettieri, T., 2016. Algal bloom and its economic impact; EUR 27905 EN; doi:10.2788/660478ences

Sathirathai, S., Barbier, E.B., 2001. Valuing mangrove conservation in Southern Thailand. Contemp Econ Policy 19, 109-122.

Scientific, Technical and Economic Committee for Fisheries (STECF). 2018. Economic Report of the EU Aquaculture sector (STECF-18-19). Publications Office of the European Union, Luxembourg. ISBN 978-92-79-79402-5. https://doi:10.2760/45076, JRC114801

Scotland's Aquaculture. 2020. Shellfish Aquaculture. Available at: <http://aquaculture.scotland.gov.uk/our_aquaculture/types_of_aquaculture/shellfish.aspx> [Accessed 21 May 2020].

Smayda, T.J., 1990. Novel and nuisance phytoplankton blooms in the sea: evidence for a global epidemic. In Granéli E., Sundstrøm B., Edler L. and Anderson D.M. (eds) Toxic marine phytoplankton. New York, NY: Elsevier, pp. 29–40.

Smayda, T.J., 2004. Harmful algal bloom communities in Scottish coastal waters: relationship to fish farming and regional comparisons - a review. Paper 2006/3. https://www.webarchive.org.uk/wayback/archive/20170701074158/http://www.gov.scot/Publications/2006/02/03095327/16

Stubbs, B., Swan, S., Davidson, K., Turner, A., Algoet, M. 2016. Annual report on the results of the Biotoxin and Phytoplankton Official Control Monitoring Programmes for Scotland – 2015. FSA 199 C5666-C5667, 155 pp. - https://www.foodstandards.gov.scot/publications-and-research/publications/annual-report-on-the-results-of-the-biotoxin-and-phytoplankton-official-con

Swan, S.C., Turner, A.D., Bresnan, E., Whyte, C., Paterson, R.F., McNeill, S., Davidson, K. 2018. *Dinophysis acuta* in Scottish Waters and its Influence on Diarrhetic Shellfish Toxin Profiles. Toxins 10(10), 399; https://doi.org/10.3390/toxins10100399

Taylor, T., Longo, A., 2010. Valuing algal bloom in the Black Sea Coast of Bulgaria: A choice experiments approach. J Environ Manage 91, 1963–1971. https://doi.org/10.1016/j.jenvman.2010.04.007.

Tett, P., Edwards, V., 2002. Review of harmful algal blooms in Scottish coastal waters. Report to SEPA, Edinburgh, Scotland, 120 pp.

Tillmann, U., Elbrachter, M., Krock, B., John, U., Cembella, A.D., 2009. *Azadinium spinosum* gen. et sp. nov. (Dinophyceae) identified as a primary producer of azaspiracid toxins. Eur J Phycol 44, 63-79.

Umar, H.S., Girei, A.A., Yakubu, D., 2017. Comparison of Cobb-Douglas and translog frontiers model in the analysis of technical efficiency in dry season tomato production. Agrosearch 17(2), 67-77.

Verbeek, M. 2017. A Guide to Modern Econometrics, 5th Edition. Wiley. Fifth edition.

Wells, M.L., Karlson, B., Wulff, A., Kudela, R., Asnaghi, V., Berdalet, B., Cochlan, W., Davidson, K., De Rijcke, M., Dutkiewicz, S., Hallegraeff, G., Flynn, K.J., Legrand, C., Paerl, H., Silke, J., Suikkanen, S., Thompson, P., Trainer, V., Trick, C. 2019. Future HAB Science: Directions and Challenges in a Changing Climate. Harmful Algae https://doi.org/10.1016/j.hal.2019.101632

Whyte, C., Swan, S., Davidson, K., 2014. Changing wind patterns linked to unusually high *Dinophysis* blooms around the Shetland Islands, Scotland. Harmful Algae 39, 365–73. Available from: http://dx.doi.org/10.1016/j.hal.2014.09.006

TABLES

Table 1A: Descriptive statistics (mean, standard deviation in parenthesis) for the productive/economic variables of Scottish shellfish industry in each region for the period 2009 to 2018. Unit of measure is ton for shellfish production, number (#) of active producing sites for capital, number of employees for labour, and number of employees per site as a measure of capital intensity.

Region	**Production (t)**	**Active sites (#)**	**Labour (#)**	**Labour/sites (#)**
Clyde	842.279 (278.89)	36.712 (5.14)	113.128 (7.86)	3.081 (0.39)
Outer Hebrides	678.670 (262.18)	19.063 (3.00)	32.841 (3.25)	1.723 (0.30)
Shetland	4,825.707 (989.56)	75.334 (16.9)	111.860 (12.18)	1.485 (0.49)
West Highland	850.315 (253.56)	28.336 (1.79)	74.224 (12.55)	2.619 (0.47)

Table 1B: Descriptive statistics (mean, standard deviation in parenthesis) for harmful algae for each region in the period 2009 to 2018. Unit of measure is the interval 0 to 1 (fraction above the critical damaging threshold as shown in the Table A0 reported in the Appendix). The Table reports also temperature and NAO index. They are common for all regions. Temperature is measured in degrees Celsius, NAO index is expressed in the interval -1 to 1.

Region	***Pseudo-nitzschia (0-1)***	***Alexandrium (0-1)***	***Dinophysis (0-1)***	***Prorocentrum (0-1)***
Clyde	0.046 (0.028)	0.136 (0.054)	0.162 (0.053)	0.011 (0.005)
Outer Hebrides	0.076 (0.047)	0.183 (0.061)	0.127 (0.079)	0.010 (0.007)
Shetland	0.171 (0.099)	0.189 (0.082)	0.148 (0.058)	0.023 (0.033)
West Highland	0.088 (0.048)	0.170 (0.068)	0.224 (0.063)	0.018 (0.013)
		SST (degrees C)	**NAO (1-1)**	
All Regions		10.395 (0.222)	0.036 (0.021)	

Table 1C: Descriptive statistics (mean, standard deviation in parenthesis) for biotoxins in each region in the period 2009 to 2018. Unit of measure is interval 0 to 1 (fraction above the critical damaging threshold as shown in the Table A0 reported in the Appendix).

Region	**ASP (0-1)**	**AZP (0-1)**	**DSP (0-1)**	**PSP (0-1)**	**YTX (0-1)**
Clyde	0.006 (0.010)	0.000 (0.000)	0.254 (0.188)	0.001 (0.001)	0.000 (0.000)
Outer Hebrides	0.006 (0.006)	0.020 (0.042)	0.223 (0.138)	0.002 (0.003)	0.002 (0.004)
Shetland	0.004 (0.005)	0.019 (0.041)	0.239 (0.196)	0.000 (0.000)	0.001 (0.001)
West Highland	0.008 (0.010)	0.015 (0.021)	0.247 (0.193)	0.002 (0.002)	0.002 (0.002)

Legend: Diarrheic Shellfish Poisoning (DSP), Paralytic Shellfish Poisoning (PSP), Amnesic Shellfish Poisoning (ASP), Azaspiracids poisoning (AZP), Yessotoxins (YTX)

Table 2: Pairwise correlation between variables. Significant correlations at alpha level 0.05 are reported with an asterisk

	Production	**Sites (capital)**	**Labour**	**ASP**	**DSP**	**AZP**	**PSP**	***Alexandrium***	***Dinophysis***	***P. lima***	***Pseudo-nitzschia***	**SST**	**NAO**
Production	1												
Sites	0.888*	1											
Labour	0.513*	0.757*	1										
ASP	-0.057	-0.131	-0.021	1									
DSP	-0.121	-0.010	-0.0348	-0.2144	1								
AZP	0.101	0.001	-0.1316	0.0326	-0.2181	1							
PSP	-0.250	-0.306	-0.1551	-0.0383	0.2183	-0.0793	1						
Alexandrium	-0.054	-0.113	-0.1096	-0.1626	0.3691*	0.0871	0.1184	1					
Dinophysis	-0.0806	0.041	0.1003	-0.0496	0.2723	0.0305	0.0482	0.1059	1				
P. lima	0.271	0.276	0.1121	0.1712	-0.0704	0.119	-0.0235	-0.133	0.0981	1			
Pseudo-nitzschia	0.54*	0.377*	0.2238	0.0795	(-)0.3413*	0.3977*	(-)0.3170*	0.0987	-0.127	-0.0441	1		
SST	0.001	0.011	-0.0472	0.1651	0.1695	-0.0944	(-)0.3314*	0.0427	-0.3028	-0.0709	0.0127	1	
NAO	-0.118	-0.031	-0.1069	-0.2176	0.699*	0.0904	0.3396*	0.2809	0.0859	0.1447	-0.2835	0.0271	1

Legend: Diarrheic Shellfish Poisoning (DSP), Paralytic Shellfish Poisoning (PSP), Amnesic Shellfish Poisoning (ASP), Azaspiracids poisoning (AZP), Yessotoxins (YTX); Sea Surface Temperature (SST); North Atlantic Oscillation (NAO)

Table 3: Vector auto regression (VAR) modelling the value of DSP as a function of lagged values of HABs, biotoxins, NAO and SST

Dep. Variable	*R-sq*	*chi2*	*P>chi2*
DSP	*0.677*	*81.699*	*0.0000*

variables	*coefficient*	*Std err*	*z*	*P>z*
DSP_L1	0.0054	0.1255	0.04	0.966
Alexandrium_L1	0.2923	0.2635	1.11	0.267
Dinophysis_L1	0.5536	0.2444	2.27	0.023
P. lima_L1	-2.0174	0.8769	-2.30	0.021
Pseudo-nitzschia_L1	-0.0184	0.2584	-0.07	0.943
ASP_L1	*-2.1901*	*2.0313*	*-1.08*	*0.281*
AZP_L1	0.2077	0.5926	0.35	0.726
PSP_L1	17.2495	9.4221	1.83	0.067
NAO_L1	0.3723	0.0685	5.44	0.000
SST_L1	0.0882	0.0915	0.96	0.335
constant	-0.8021	0.9448	-0.85	0.396

Legend: Diarrheic Shellfish Poisoning (DSP), Paralytic Shellfish Poisoning (PSP), Amnesic Shellfish Poisoning (ASP), Azaspiracid poisoning (AZP), Yessotoxins (YTX); Sea Surface Temperature (SST); North Atlantic Oscillation (NAO). L1 stands for lag 1.

Table 4a: Cobb-Douglas production function estimated by random effect estimator with instrumental variables. Dependent variable: shellfish production. Instrumented variables: DSP - Instruments: sites, labour, SST, NAO, *Dinophysis*. Analysis carried out using clustered robust errors.

variables	coefficient	Robust Std err	t	P>t
Sites	1.889	.108	17.40	0.000
Labour	-.633	.145	-4.37	0.000
DSP	-.914	.318	-2.87	0.004
Constant	3.351	.404	8.29	0.000
N obs *40*	Wald chi2(2) 1220.37	R2 within 0.400	R2 between 0.982	R2 overall 0.858
N groups *4*	Prob>chi2 0.000			

Table 4b: First stage regression estimated by random effect estimator. Dependent variable: DSP - Instruments: sites, labour, SST, NAO, *Dinophysis.*

variables	coefficient	Robust Std err	t	P>t
Sites	-.0149	.0523	-0.29	0.776
Labour	.0185	.0513	0.36	0.718
NAO	.437	.0520	8.40	0.000
SST	.195	.0911	2.15	0.032
Dinophysis	.699	.287	2.44	0.015
Const	-1.952	.955	-2.04	0.041
	Wald chi2(5) 117	Prob>chi2 0.000		
	N obs 40	N groups 4		

Table 5a: Cobb-Douglas production function estimated by 2SLS estimator with dummy variables and instrumental variables. Dependent variable: shellfish production. Instrumented variables: DSP - Instruments: sites, labour, SST, NAO, *Dinophysis*. Clustered robust errors are shown.

variables	coefficient	Robust Std err	t	P>t
Sites	.959	.265	3.62	0.000
Labour	-.122	.277	-0.44	0.660
DSP	-.661	.241	-2.74	0.006
Constant_A (Clyde)	4.024	1.924	2.09	0.037
Outer Hebrides	.241	.442	0.54	0.586
West Highlands	.202	.157	1.29	0.197
Shetland Islands	1.044703	0.187	5.57	0.000
N obs *40*	Wald chi2(6) 877.48	R2 0.9277		
N groups *4*	Prob>chi2 0.000			

Table 5b: First stage regression for the 2SLS regression with instrumental variable reported in Table 5a. Dependent variable: DSP. Instruments: sites, SST, NAO, *Dinophysis*, Clyde, Outer Hebrides, West Highlands, Shetland Islands.

variables	coefficient	Robust Std err	t	P>t
Sites	-.1352	.127	-1.06	0.298
Labour	.1297	.168	0.77	0.447
NAO	.443	.071	6.27	0.000
SST	.247	.094	2.63	0.013
Dinophysis	1.060	.329	3.22	0.003
Constant (A) Clyde	-2.627	1.410	-1.86	0.072
Outer Hebrides	.0772	.226	0.34	0.735
West Highlands	-.052	.077	-0.69	0.498
Shetland Islands	.098	.136	0.72	0.478
N obs	F(8,31)	R2		
40	18.74	0.621		
N groups	Prob>F			
4	0.000			

APPENDIX

Table A0: harmful threshold concentration for harmful algae and biotoxins

Toxin	Type of toxin	Syn-drome	Species	Group	Threshold cells/ litre	Biotoxin
Saxitoxin	Neurotoxin	PSP	*Alexandrium* sp	Dino-flagellate	40	>800 µg STX eq. / kg
Okadaic acid and derivatives	Gastro-intestinal	DSP	*Dinophysis sp*	Dino-flagellate	100	>160µg OA eq. / kg
			Prorocentrum lima	Dino-flagellate		
Domoic acid	Neurotoxin	ASP	*Pseudo-nitzschia sp.*	Diatom	50 000	>20 mg DA/kg
Yessotoxin (YTX)			*Prorocentrum reticulatum,*	Dino-flagellate	100	>3.75mg YTX eq./kg
Azaspiracid (AZA)	Gastro-intestinal	AZP	*Azadinium sp*	Dino-flagellate		>160ug AZA eq./kg

Table A1: Augmented Dickey-Fuller test (1979) tests the stationarity of the variables of the panel. Null Hypothesis: variable is not stationary.

Variable	**ADF Z test statistics**
Production	-2.131(0)* drift
Active sites	-2.51(1)* drift
Labour	-8.53(0)** trend
SST	-3.81(0)* drift
NAO	-5.28(0)** trend
ASP	-3.009(0)** drift
AZP	-4.55(1)** trend
DSP	-1.60(0) #drift
PSP	-3.005(0)** drift
YTP	-1.69(0)# drift
Alexandrium spp	-2.384(0)* drift
Dinophysis spp	-2.884(0)* drift
Prorocentrum spp	-2.041(0)* drift
Pseudo-nitzschia spp	-2.74(1)* drift

In bracket it is reported the optimal lag;
Drift= stationarity around a constant mean
Trend=stationarity around a trend
# significant at 0.10;
* significant at 0.05;
** significant at 0.01