Quantifying the impact: Are coastal areas impoverished by marine pollution?*

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Abstract

We propose a methodological framework to assess the causal impact of Harmful Algal Bloom (HAB) events on economic indicators at a territorial level, with special consideration for spatial effects. Using the Mar Menor region in Spain as a case study, we empirically apply our framework. Our findings indicate a significantly negative causal effect of marine pollution resulting from HAB events on income per capita at the census section level. We observe that this effect is exacerbated by spatial interactions among neighboring census sections adjacent to those directly affected by seawater degradation. These results underscore the importance of implementing effective environmental regulations to mitigate seawater pollution and proactive measures to safeguard the well-being of local populations. Our research provides valuable insights for future studies in similar coastal regions.

Keywords: Harmful algal bloom, coastal ecosystem, seawater deterioration, externalities, spatial difference-in-differences.

JEL Classification: Q53, D62, C21.

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1. Introduction

Addressing the relationship between marine deterioration and income is of utmost significance, given that more than one-third of the global population resides in coastal areas (Barbier, 2017). According to Costanza et al. (1998), these coastal regions are immensely valuable as they provide a wide array of ecosystem services, encompassing various goods and services. Notably, Zamboni et al. (2021) emphasized that the conservation of marine and coastal ecosystems has resulted in a rapidly expanding assortment of economic valuations worldwide.

The major threats to marine-coastal ecosystems are anthropogenic pressures, primarily arising from intensive agricultural activities and urban development along the coast. Moreover, climate change is worsening the situation, with more frequent floods and rising temperatures intensifying the impact of human activities on ecosystems. Of particular interest for this study is the environmental distortions caused by the excessive nutrient input from agriculture, which can result in eutrophication of seawaters. In extreme cases, eutrophicated ecosystems suffer from algae blooms, which have a wide range of negative consequences on marine environments. Certain types of harmful algal blooms (HABs) pose serious risks for human and animal health. At the same time, HABs cause the waters turned turbid and greenish, making them easily visible for residents and visitors of coastal destinations.

Hoagland and Scatasta (2006) demonstrated that the occurrence of HABs imposes substantial economic burdens worldwide. In Europe, they estimated these costs at approximately 813 million euros annually, encompassing expenses related to public health, commercial fisheries, recreation, tourism, and monitoring and management. Therefore, it is imperative to understand the economic impact of environmental degradation to prioritize national and regional efforts and advocate for the implementation of ecosystem protection measures, some of which remain underdeveloped (Groeneveld et al., 2018).

In this context, it is crucial to develop robust methodologies for comprehensively assessing the economic effects of marine pollution, including HABs. By addressing this challenge, the aim is not only to grasp the magnitude of economic losses but also to inform environmental management decision-making and public policy to mitigate and prevent these impacts. This study proposes a methodological approach to evaluate the economic impact of

HABs and marine pollution, aiming to provide an analytical framework that can be applied in diverse coastal contexts.

To accomplish this objective, we adopt the approach proposed by Dubé et al. (2014) to modify the difference-in-differences (DID) framework, allowing for the incorporation of spillover effects resulting from spatial characteristics (SDID). By employing this method, we aim to capture the potential influence of neighboring areas on economic indicators. The rationale behind extending the traditional DID framework to incorporate spatial effects stems from the interconnected nature of coastal ecosystems. These ecosystems function as integrated systems and can experience disruptions in their equilibrium due to HABs, thereby affecting adjacent regions.

Factors such as economic interdependencies, the interconnectivity of coastal ecosystems, and water circulation patterns collectively contribute to the potential spread and amplification of the pollution's impact. By examining not only the direct effects but also the spatial spillovers, we can more accurately assess the actual causal effect of coastal deterioration on economic indicators. This is crucial as examining only direct effects may underestimate the actual extent of the causal effect.

In order to test the adequacy of our proposal, we develop an empirical application focused in the Mar Menor, in Spain, utilizing micro-territorial data obtained for census sections. While previous studies have identified a positive association between the economic values of ecosystem services and gross domestic product (Zamboni et al., 2021), to the best of our knowledge, we are the first to attempt quantifying the impact of marine deterioration on income per capita.

The interest in the Mar Menor stems from its ongoing and critical eutrophication crisis. Our empirical findings suggest a significantly negative influence on annual income per capita for the census sections affected by the HAB in comparison to the non-coastal territories following the contamination of the Mar Menor. The presence of marine pollution is associated with a direct decrease of 6.7% in income per capita. Additionally, when the affected coastal section is surrounded by other territories impacted by seawater pollution, there is an additional decrease of 11.4% in income per capita. This indicates that pollution spillover from neighboring areas intensifies the negative economic consequences on the affected coastal census sections. Considering both the direct and indirect effects, the total causal effect of the 2016 harmful algal bloom event is estimated to be a substantial decrease of 18.1% in income per capita. In monetary terms, this translates to a substantial total income loss of 97.21 million euros the Mar Menor HAB.

The following section presents a literature review that examines the economic impact of HABs and provides an overview of the case of eutrophication in the Mar Menor. Section 3 describes the methodological approach employed in this study. Section 4 presents the case study of Mar Menor, including the datasets and empirical results. Finally, Section 5 delves into the discussion, conclusions, and policy recommendations.

2. Background literature

2.1. Harmful algal blooms

Over the past four decades, there has been a notable increase in the frequency, severity, and extent of eutrophication worldwide (Ho et al., 2019). According to Sandifer et al. (2021), eutrophication is primarily attributed to the extensive use of nitrogen and phosphorus fertilizers in intensive agricultural and livestock activities. Alongside nutrient pollution from urban areas, these practices have been identified as the main threats to both freshwater and marine ecosystems (Gilbert and Burford, 2017). Under exceptional circumstances, eutrophicated ecosystems experience algae blooms in inland and coastal waters. Algae blooms refer to the excessive growth of microalgae in marine or saltwater environments, which can result in marine anoxia, massive fish mortality, seafood toxicity, and even human health issues (UNESCO/IOC Project, 2021).

2.2. The economic impact of HAB

Extensive literature states that healthier seawater ecosystems strength the economic activity in surrounding coastal regions. However, Hoagland and Scatasta (2006) observed that there is a relatively fewer number of studies focusing on the economic costs associated with HABs. This is surprising considering the significant expenses that can arise from HAB events. For instance, HABs can pose public health risks (Young et al., 2020), particularly through the consumption of contaminated seafood or exposure to algal toxins via inhalation or skin contact (Berdalet et al., 2016). Furthermore, HABs can impede recreational and tourist activities (Morgan et al., 2009), increase the costs of water monitoring and treatment (Park et al., 2013), disrupt commercial uses such as fisheries (Weir et al., 2022), and result in the loss of aesthetic and cultural value (Willis et al., 2018).

Hoagland and Scatasta (2006) identified four primary reasons that explain this research deficiency: a lack of data on HAB events, the infrequency of their occurrence in many areas, the limited scale of their economic effects, and the high costs associated with conducting appropriate studies, often involving survey design. Consequently, Groeneveld et al. (2018) highlighted that most existing studies aiming to estimate the economic losses of HABs rely on value assessments based on stated preferences of respondents. Examples of such studies include Dyson and Huppert (2010), Zhang et al. (2022), and Boudreaux et al. (2023).

Conversely, studies that examine the costs of HABs using actual observational data are much less common. A few notable examples include Larkin and Adams (2007), who utilized time series information from the Florida Department of Revenue (FDOR) to analyze the impact of HAB events on business revenues in the restaurant and lodging sectors along the northwest coast of Florida between 1996 and 1999. Their findings revealed a direct reduction of 29% to 35% in average monthly revenues attributed to these events. Additionally, Zhang et al. (2022), leveraging nationwide data on property values in the United States, discovered robust evidence for the Upper Midwest and South regions, demonstrating that the frequency of cyanoHABs diminishes the capitalized value of amenity and recreation services for near-shore homes. Sampat et al. (2021) examines the economic impacts of harmful algal blooms (HABs) caused by nutrient pollution from livestock waste, proposing a computational framework to quantify these impacts. They highlight the importance of assessing the environmental and socioeconomic effects of phosphorus pollution in affected regions, such as the case of the Upper Yahara watershed area in Wisconsin. The study reveals that every excess kilogram of phosphorus runoff from livestock waste in this region results in total economic losses of 74.5 USD, driving the need to manage waste in a sustainable manner to effectively reduce nutrient pollution.

3. Methodological proposal

We utilize a quasi-natural experiment approach, leveraging longitudinal data from designated treatment and control groups. The objective is to estimate the causal effect of seawater pollution on an economic variable, with a specified break date. By harnessing the extensive dataset available, we can accurately evaluate the impact of marine pollution on income in coastal regions.

3.1. Difference-in-Differences Model in the HAB context

Difference-in-Differences (DID) is a robust econometric approach commonly used to evaluate causal effects of interventions or events on a specific outcome variable. In our proposal, we consider two distinct groups: the treatment group, which comprises territories directly affected by the HAB event, and the control group, consisting of unaffected or less affected regions. Additionally, we introduce the occurrence of an event that could further differentiate between the control and treatment groups. The standard DID model is structured as follows:

$$Y_{it} = \alpha_0 + \alpha_1 Time_t + \alpha_2 Treat_i + \alpha_3 (Time_t Treat_i) + X_{it}\beta + \varepsilon_{it}, \qquad (1)$$

where Y_{it} is the economic variable which causal effect is examined in the territory i, with $i = 1, \dots, N$, at time period t.

In this expression, the intercept α_0 signifies the average value of the explanatory variable in the control group before the treatment. The coefficient α_1 captures how much the average outcome of the control group has changed in the post-event period. Additionally, α_2 indicates the difference between the treatment and control groups before the HAB event. The row vector X_{it} represents the set of control variables, and the column vector β determines whether these covariates on the explanatory variable Y_{it}. The error term ε_{it} is assumed to be independently and identically distributed with a normal distribution with mean zero and finite variance σ^2. Of particular importance for this analysis is the interaction term $Time_t Treat_i$, which is a dummy variable that takes a value of 1 exclusively for the treatment group during the post-event period. The coefficient α_3 associated with this term captures the causal effect of the examined event on the economic variable. A statistically significant and negative coefficient would indicate a detrimental impact of the HAB event on the economic variable in the treatment group compared to the control group.

As noted by Rubin (1978, 1990), a key assumption needed for identification of causal effects in the linear DID stated in (1) is the stable unit treatment value assumption (SUTVA). This implies that potential outcomes for territory i are unrelated to the treatment status of other territories. Due to the design of our quasi-experiment, the HAB event specifically affects territories delineated by geographic boundaries. Consequently, there are reasons to expect that the treatment effects may spill over onto neighboring units in closer proximity. Firstly, coastal areas often share economic interdependencies, such as tourism, fisheries, and recreational activities. When seawater pollution occurs in a specific coastal territory, neighboring units may experience indirect economic repercussions. For example, a decline in tourism or a decrease in fishery productivity in one area can have adverse effects on the tourist services provided by nearby census sections.

Secondly, seawater pollution can trigger ecological feedback mechanisms that exacerbate the spread of pollution. For instance, excessive nutrient inputs can fuel algal blooms, which in turn deplete oxygen levels in the water, leading to further ecological degradation. These cascading effects can extend to neighboring units and contribute to the propagation of spillover effects. Thirdly, coastal territories often share water bodies, such as bays or estuaries, which can facilitate the transport of pollutants. Seawater pollution in one area can be carried by water currents or tidal movements to adjacent regions, leading to contamination and environmental degradation in these neighboring units.

Thus, the presence of these potential spatial spillovers in this analysis would violate the SUTVA assumption. To ensure the validity of our findings, it is necessary to explicitly consider space in this context and integrate spatial relationships directly into the traditional DID approach. With this purpose, we use a weighting matrix W of known constants, which represents the spatial connectivity structure among the examined territories. In the case we compare two pre and post event years, then W is the row standardized version of a $2N \times 2N$ binary matrix where the $w_{(i,j)}$ element is set to 1 if j is one of the K nearest neighbors of i, indicating spatial adjacency; otherwise, it is set to 0.[1]

3.2. Spatial DID model in the HAB event.

In spatial econometric literature, several spatial specifications have been developed to account for spatial spillover effects (Pace and LeSage, 2009; Elhorst, 2014). These specifications aim to address the spatial correlations caused by dependent variables, the error term, and independent variables in the model. The models that incorporate these spatial effects are commonly known as the spatial autoregression (SAR) model, the spatial error model (SEM), and the spatial Durbin model (SDM), respectively. Following, for example, Chagas et al. (2016), Diao et al. (2017), Qiu and Tong (2021) or Sunak and Madlener (2016), we consider these three specifications of spatial difference in differences models (SDID) that account for treatment effects estimation in settings with spatial dependence.

The first version of SDID that we consider is based on SAR models:

[1] As is customary in spatial analysis, it is assumed that the diagonal entries of W are zero.

$$Y_{it} = \alpha_0 + \alpha_1 Time_t + \alpha_2 Treat_i + \alpha_3 (Time_t Treat_i) + \rho(WY)_{it} + X_{it}\beta + \varepsilon_{it}, \quad (2)$$

where $\rho \in [-1,1]$. This specification incorporates the spatially weighted dependent variable as an endogenous regressor on the right-hand side of the standard DID equation ($\rho(WY)_{it}$). It assumes that the economic indicator of the territory i is directly influenced by the spatially weighted dependent variable of neighboring territories denoted as j. The error term ε_{it} is assumed as in (1).

The second version of SDID that we consider relies on SEM models:

$$\begin{gathered} Y_{it} = \alpha_0 + \alpha_1 Time_t + \alpha_2 Treat_i + \alpha_3 (Time_t Treat_i) + X_{it}\beta + u_{it}, \\ u_{it} = \delta(Wu)_{it} + \varepsilon_{it}. \end{gathered} \quad (3)$$

In this equation, u represents a vector that combines the error terms across all the census sections $i = 1, \dots, N$, for pre and post HAB event years t. Unlike equation (2), specification (3) explicitly incorporates the modeling of spatial autocorrelation between the disturbances, quantified by the scalar parameter δ. In this case, the spatial correlation between territories would be caused by unobserved characteristics, which are independent of the included covariates. The error term ε_{it} is assumed as in (1).

Finally, we explore a third approach that incorporates spatial dependence in the DID framework, based on the SDM model:

$$\begin{aligned} Y_{it} = {} & \alpha_0 + \alpha_1 Time_t + \alpha_2 Treat_i + \alpha_3 (Time_t Treat_i) + \rho(WY)_{it} + X_{it}\beta \\ & + (WX)_{it}\gamma + \varepsilon_{it}, \end{aligned} \quad (4)$$

where X is the $tN \times \mathrm{K}$ matrix stacking the covariates across all the territories for pre and post event years t and K represent the number of explicative variables. This specification extends the SAR model by including spatially lagged covariates. Apart from the spatially weighted dependent variable, it allows for the inclusion of both direct effects β of the covariates and indirect spillover effects γ from the neighboring census sections' covariates. As in (1), ε_{it} follows an independent normal distribution with a mean of zero and a finite variance of σ^2.

It is widely recognized that direct interpretations of impacts through partial derivatives are not valid in spatial analyses (LeSage and Pace, 2009). To illustrate this, let's consider the Durbin-related version of SDID models as a reference, expressed in matrix form:

$$y = \rho \mathrm{W}\mathrm{y} + X^*\beta^* + \mathrm{W}\, X^*\gamma^* + \varepsilon. \quad (5)$$

In equation (5), X^*expands X by adding four columns: a column vector of ones, a vector stacking the values of the time dummy variable, a stacked vector of the treatment dummy variable, and a stacked vector of the multiplicative dummy. In a spatial Durbin model, a change in a particular explanatory variable k in census section i has a direct effect on that census section, but also an indirect effect on the census sections.

Specifically, the matrix of partial derivatives of y at the census section *i* at time *t* with respect to the kth explanatory variable of X^* at the census section *j* at time *t* can be obtained as:

$$\begin{bmatrix} \frac{\partial y_1}{\partial x_{1k}} & \cdots & \frac{\partial y_1}{\partial x_{2nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_n}{\partial x_{1k}} & \cdots & \frac{\partial y_n}{\partial x_{2nk}} \end{bmatrix} = (I_{2N} - \rho W)^{-1} \begin{bmatrix} \beta_k^* & \cdots & \omega_{1,2n}\gamma_k \\ \vdots & \ddots & \vdots \\ \omega_{2n,1}\gamma_k & \cdots & \beta_k^* \end{bmatrix}, \tag{6}$$

where I_{2N} is an *2N*-dimensional identity matrix. The coefficient β_k^* captures the direct effect, quantifying the change in the economic variable y in the territory i resulting from a specific change. However, there is an additional effect to consider: the average effect on the territory i due to changes in the explanatory variables of the territories j (where $j \neq i$). This indirect effect is represented by the coefficients $\omega_{i,j}$ and γ_k, where $\omega_{(i,j)}$ represents the (i,j) element of the weight matrix W. The total effect is obtained by summing the direct and indirect effects.[2]

4. Empirical application: The case of Mar Menor

The Mar Menor (Spain), the largest coastal hypersaline lagoon in the Mediterranean basin, suffers from eutrophication due to the nutrients that receives from intensive agriculture at the Campo de Cartagena watershed (Álvarez-Rogel et al., 2020) and, to a lesser extent, from urban wastewater altering its ecological state (Ruiz-Fernández, 2019). Studies have shown negative economic impacts, such as decreasing housing prices and the risk of business failure in the area (Lamas et al., 2023; Mate-Sanchez-Val and Aparicio-Serrano, 2023). Marine pollution has led to a reduction in Airbnb rental prices and tourists' willingness to switch to less contaminated municipalities (Fernández Ferrero et al., 2022). The importance of

[2] In SEM models, the matrix of the right-hand term of (6) is a diagonal matrix with elements equal to β_k^*. In SAR models, the main diagonal of this matrix contains null elements.

implementing effective environmental regulations to mitigate pollution in the Mar Menor and protect the local economy is emphasized (Alcon et al., 2021; Alcon et al., 2022).

4.1. Data

In this section, we introduce the study case in the Mar Menor. In particular, we investigate the causal effect of seawater deterioration on the income per capita using a SDID approach. In addition we collect spatial data and quantitative variables. The spatial data allows us to identify the specific territorial units affected by seawater deterioration, which we classify as treatment spatial units. We select census section as the level of disaggregation in this analysis. This choice allows for detailed analysis of smaller geographical areas and facilitates data comparability, targeted policy development, and social issue identification.

4.1.1. Treatment and control group

We have limited our sample to the Region of Murcia as the Mar Menor lagoon falls administratively within this region, excluding other coastal regions in Spain that might be affected by distinct pollution events (see Figure 1). The impact of seawater pollution affects mainly the coastal census sections of the Mar Menor lagoon, which are identified as the treatment group. The census sections located further inland are not exposed to treatment and belong the control group.

We distinguish the observations belonging to the treatment group, encompassing areas directly affected by the seawater deterioration event, by generating a binary dummy variable termed $Treat_i$. This variable takes a value of 1 to indicate the presence of treatment or exposure to the seawater pollution, while a value of 0 denotes the absence of pollution affects. To visualize the geographical distribution of census sections in the treatment group ($Treat_i = 1$) distinct from the control group ($Treat_i = 0$), we have highlighted the census sections that belong to the treatment group in light blue color on Figure 2.

4.1.2. Turning point date

To implement a DID approach with a temporary event determined by deterioration of the Mar Menor lagoon, we require to consider both pre and post stages surrounding the occurrence of the seawater pollution event. This necessitates establishing a specific period to demarcate the transition between these two stages.

For this purpose, our study focuses specifically on the concentration of chlorophyll-a as a crucial indicator for monitoring phytoplankton and assessing the ecological status of water bodies. Elevated chlorophyll-a levels often indicate the presence of cyanobacteria blooms, which are instrumental in understanding the overall health of marine ecosystems. Previous research by Aguilar et al. (2016) has demonstrated a notable increase in chlorophyll-a concentration during the 2000s in the Mar Menor. However, a significant turning point occurred in the summer of 2016, marking a distinct transformation in the Mar Menor. Since then, the seawater has exhibited diverse dynamics of water quality, characterized by varying appearances of greenish and turbid conditions.

Monitoring the water quality in the Mar Menor lagoon has greatly benefited from the detection of chlorophyll-a concentration using satellite imagery (Mate-Sanchez-Val and Aparicio-Serrano, 2023). Leveraging sensing data from the European Space Agency's Sentinels-2 and 3 satellites, Figure 3 showcases an August 2016 satellite image that vividly illustrates the exceptional levels of chlorophyll-a concentration in the Mar Menor starting in 2016. This situation of an abnormal content of chlorophyll-a and turbidity in the Mar Menor waters persisted until 2018 (IEO, 2020).

Given this evidence, we designate the period 2016-2018 as the pivotal turning period for our DID model. To account for this issue in a DID model, we create a binary indicator (variable $Time$), which captures the temporal effect by indicating whether the observation is in the post-event stage ($Time = 1$) or pre-event stage ($Time = 0$).

4.1.3. Income per capita and control variables

To gather data on income per capita at a detailed level of census section disaggregation, we utilize the Household income distribution map dataset provided by the National Institute of Statistics of Spain (INE). This dataset contains annual data starting from 2015 and allows us to examine income patterns at the census section level. Our dependent variable is the natural logarithm of the income per capita in Euros (variable *income*).

As control variables, we choose a set of demographic and economic factors that are available at census section level. Specifically, we use the percentage of residents of foreign nationality (variable *foreign*); the natural logarithm of the population per square kilometer (variable *density*); the Gini index expressed as a percentage, which measures income inequality (variable *gini*); the working population, measured as the percentage of people between 16 and 64 years old (variable *working*); and the proportion of the labor force that is unemployed (variable *unemployment*). By including these control variables in the analysis, the aim is to account for potential confounding factors that may influence income and to isolate the specific impact of Mar Menor pollution on income.

By merging the available data, we construct a dataset comprising 1,914 observations for two distinct time periods: pre-event (2015) and post-event (2019), with the HAB event occurring in 2016. This temporal division enables us to compare income levels before and after the occurrence of the harmful algal bloom. Table 1 provides a summary of the selected variables, making distinction between the census sections of the control group and those of the treatment group. The mean and standard deviations serve as statistics to provide a descriptive overview, providing insights into the characteristics of the dataset and facilitating a preliminary understanding of the income dynamics associated with the studied time periods.

4.2. Results

4.2.1. Exploratory spatial data analysis

In order to examine potential spatial patterns in the distribution of income per capita among the census sections of the Spanish autonomous community of Region de Murcia, we conducted an exploratory spatial data analysis. This analysis holds significance as the identification of spatial patterns would question the assumptions made by the classical DID model and provide rationale for incorporating a spatial version of this methodology.

To begin, we present in Figure 4 a choropleth map displaying the income per capita distribution across census sections, with territories categorized into quartiles based on their income levels. This visual representation effectively showcases the spatial distribution of income, highlighting regions with high, medium, and low income per capita. By examining the quartiles, we discern clear indications of spatial association in the distribution of income per capita across the study area.

Furthermore, we rigorously examine the significance of the spatial distribution by conducting tests for spatial autocorrelation in income per capita and other explanatory variables. Spatial autocorrelation measures the extent to which values of a variable exhibit correlation with neighboring values. This analysis enables us to identify the presence of spatial associations, indicating that territories with similar levels of the analyzed variable are geographically clustered. To accomplish this, we employ the Moran's I test, utilizing different spatial weighting matrices defined through the *k*-nearest neighbor's approach.

Table 2 shows that the Moran's I statistic not only for the dependent but also for the control variables is statistically significant at the 1% level. This indicates the presence of spatial correlation among income per capita, the proportion of foreign residents, population density, inequality, the proportion of working population, and unemployment across census sections within the region. In terms of the sign of the statistic, we observe that all variables exhibit positive spatial correlation. Notably, income per capita, the dependent variable, displays the strongest spatial correlation in terms of magnitude. These findings provide a strong justification for estimating the SDID model.

4.2.2. Spatial Difference in Differences model (SDID) results

Despite the spatial patterns detected with the exploratory spatial data analysis, to enable a comprehensive comparison and further validate our findings, we present in this section the results of both DID and SDID approaches. Including DID can evaluate the differential effects and examine whether the spatial component significantly improves the model's explanatory power, which enables a more informed interpretation of the results. Both, DID and SDID models, are estimated at census section territorial level of aggregation considering the HAB event during the period 2016-2018 and as pre and post stages during the years 2015 and 2019, respectively.

The standard DID estimator is assessed in the second column of Table 3. The estimated treatment effect, represented by the parameter capturing the interaction between the $Time$ and $Treat$ dummies, suggests a negative influence of approximately 7% on income per capita for the census sections affected by the HAB in comparison to the control group following the contamination of the Mar Menor. However, it is crucial to note that this impact does not reach statistical significance based on the standard specification.

All control variables exhibit statistical significance at the 1% and their signs align with our expectations. A higher proportion of foreign-born individuals is associated with a decrease in average income per capita, as evidenced by a decrease of 0.7% for every 1% increase in the percentage of foreign-born residents. This negative relationship is in line with previous literature on the labor market, which has found that foreign residents often hold lower-wage positions. This is because individuals from foreign backgrounds frequently encounter barriers to accessing higher-paying employment opportunities due to factors such as language proficiency, recognition of foreign qualifications, or discrimination in the labor market (Kerr and Kerr, 2011; Ubalde and Alarcón, 2020). Therefore, the higher proportion of foreign-born residents within these coastal regions may contribute to downward pressure on the average per capita income of the surveyed territory, reflecting the prevalence of lower-paying positions held by this demographic group.

Conversely, population density displays a positive association with income per capita. The coefficient for the Gini index regression reveals that a one-unit increase in the Gini Index is associated with a 0.91% increase in residents' income. This suggests that a more unequal distribution of income is associated with a higher overall income level. Income inequality and a higher overall income level can coexist within a community. For example, consider a small town with two residents: Person A earns $10,000 per year, and Person B earns $50,000 per year. Despite the income disparity between Person A and Person B, the total income for the community is $60,000, resulting in an average income of $30,000. In this scenario, the unequal distribution of income, with Person B earning significantly more than Person A, contributes to the higher overall income level within the population. Lastly, as anticipated, unemployment is significantly and negatively associated with income per capita.

To evaluate the need for spatial extensions in the Difference-in-Differences (DID) model, the first column of Table 4 presents the Lagrange Multiplier (LM) tests and their robust versions (RLM). These tests assess whether the inclusion of spatial terms significantly enhances the model's fit by comparing the likelihood of a model with spatial dependence to a model without spatial dependence. Specifically, the table displays the Lagrange Multiplier test results for spatial lag dependence (LMlag and RLMlag) and spatial error dependence (LMerr and RLMerr). The significance of these tests confirms the existence of a spatial dependence structure in the DID model, indicating the necessity for spatial extensions.[3]

Building upon the findings, Table 3 presents the estimation outcomes of the SDID model incorporating a spatial Durbin structure (SDM). This model specification serves as an appealing initial framework for spatial econometric modeling due to its ability to facilitate a top-down model selection approach (Floch and LeSaut, 2018). By employing likelihood ratio tests, we can effectively identify the most suitable model specification to capture the dataset's characteristics.

The SDID model with spatial Durbin structure encompasses the other well-established specifications in the literature as special cases. When $\gamma = 0$, the model reduces to the spatial lag model (SAR), while a simplification of SDM arises when $\gamma = -\rho\beta$, leading to the spatial error model (SEM). Furthermore, the model accommodates the DID specification that does not account for spatial patterns when $\rho = 0$ and $\gamma = 0$. Specifically, an examination of the first four rows of results presented in Table 4 overwhelmingly suggest the effectiveness of

[3] Throughout this section, we present the results using a weighting matrix based on the 4-nearest neighbor's approach. It is important to note that the findings remain robust across *k* values ranging from 1 to 5.

employing. In addition, the findings in the last four rows strongly favor the use of the spatial Durbin structure.

The third column of Table 3 presents the empirical results of the SDID model incorporating a spatial Durbin structure. The spatial autoregressive parameter ρ is estimated to be precisely 0.675. This positive and statistically significant estimate firmly confirms the presence of spatial autocorrelation in income among the census sections. In addition, the spatial lags of these explanatory variables are also significant. These findings underscore the significance of incorporating spatial effects when examining the causal impact of the 2016 HAB event on income per capita, enhancing the accuracy and validity of the analysis.

The SDID estimation provides robust evidence that marine pollution induced by the HAB event in 2016 has a detrimental causal impact on income per capita due to the negative sign estimated for the parameter of the multiplicative dummy $Time * Treat$. The positive coefficients associated with the Time and Treat dummies signify a favorable average change in income per capita over time for the control group and a positive average difference in income per capita between the treatment and control groups before the occurrence of the HAB event, respectively. Furthermore, the parameters of the control variables exhibit the anticipated signs and all of them are statistically significant, reinforcing their role in influencing income per capita. These results align with the expectations established by the standard DID model.

4.2.3. Direct and indirect marginal effects

The marginal effects are not directly interpretable from the previous SDID model given the significance of the spatial structures (Pace and Le Sage, 2009). Applying equation (6), we compute the direct and indirect marginal effects to be able to interpretate the coefficients. The direct impacts quantify the changes in income per capita within the same census district resulting from variations in a specific explanatory variable. These effects provide insights into the immediate influence of the variable on income per capita within the focal district. In contrast, the indirect impacts assess the repercussions on income per capita in neighboring census districts due to changes in the explanatory variable. These effects capture the spillover or diffusion effects, reflecting how variations in the corresponding explanatory variable spill over to impact income per capita in nearby districts. To obtain a holistic understanding of the overall impact, the total impacts are computed as the combined sum of both direct and indirect effects.

Table 5 shows marginal effects to capture the comprehensive consequences on income per capita. These results indicate that marine pollution has had a significant impact on the income per capita in the Mar Menor coastal census sections. Specifically, the direct effect of the causal term, captured by the interaction between $Time$ and $Treat$ dummy variables, reveals that the presence of marine pollution has led to a decrease of 6.7% in the income per capita in the affected areas. Moreover, our analysis reveals an interesting indirect effect when considering the spatial context. When the coastal section affected by marine pollution is surrounded by territories also impacted by seawater pollution, the income per capita experiences an additional decrease of 11.4%. This suggests that the spillover effects of pollution from neighboring areas exacerbate the negative economic consequences on the affected coastal census sections.

Taking into account both the direct and indirect effects, the total effect of the harmful algal bloom event in 2016 is estimated to be a substantial decrease of 18.1% in income per capita, when comparing the coastal census sections of the treatment group with the inland census sections of the control group before and after the seawater event. This highlights the significant economic implications of the HAB event on the well-being of the local population and underscore the importance of addressing and mitigating marine pollution to preserve and protect the economic vitality of the Mar Menor coastal region. Implementing targeted measures to reduce pollution not only benefits the affected areas directly but also helps prevent the spillover effects on neighboring territories, thereby safeguarding the overall economic well-being of the coastal communities.

In relation to the explanatory variables, the coefficient for the time effect suggests a positive trend in income per capita of 10.6% in the absence of the treatment, which aligns perfectly with the observed data patterns. The coefficient for the treatment effect indicates a total average difference of 10.1% in income per capita between the census districts located along the coast of Mar Menor and the control group of other census districts prior to the occurrence of seawater pollution. Although this difference is not statistically significant.

While of secondary importance to the analysis conducted in this study, the findings presented in Table 5 shed light on additional insights. Specifically, a higher proportion of foreign-born residents is found to have a negative association with the overall income level, highlighting the dominance of lower-wage positions among this demographic group.

The unemployment variable also presents significant and negative marginal effects, supporting the results from previous research (Paul and Bagchi, 2023). The negative sign of the indirect effect of these variables suggests that an increase in the percentage of unemployment or/and foreign-born residents among neighboring census sections leads to a decrease in income for the census section under examination. Conversely, variables such as population density and the Gini Index present a positive impact on income.

The central question addressed in this paper is whether and by how much marine pollution has led to the economic impoverishment of the surrounding population. To answer this question, we have examined the direct, indirect, and overall effects of the 2016 HAB. The total income reduction experienced by the Mar Menor population in comparison to the control area is 18.1%, equating to a loss of 97.21 million euros, with 35.98 million from the direct impact and 61.23 million from the indirect impact. This represents a significant loss, particularly when considering that the total annual gross income of the census sections exposed to the HAB amounts to 537.05 million euros, resulting in a loss of 5,190 euros per affected household.

5. Discussion and conclusions

The tradeoff between environmental sustainability and economic development is a persistent challenge faced worldwide. This dilemma is particularly relevant in coastal regions, where the delicate balance between preserving the environment and fostering economic growth is of utmost importance. The Mar Menor coastal lagoon, situated along the Mediterranean Spanish coast, serves as an emblematic example of this global issue. In this context, our study aims to examine the causal impact of the eutrophication crisis, commonly referred to as 'the green soup,' which occurred during the summer of 2016 and persisted until 2018, on the income of residents in the Region of Murcia, SE Spain. By exploring spatial extensions of difference-in-differences models our research seeks to provide insights into the causal economic implications for this local seawater population and contribute to the broader understanding of sustainable economic development in coastal areas.

Our findings reveal a substantial total decrease in income per capita of approximately 18.1% in the area affected by marine pollution resulting from the 2016 algae bloom, which marked a break date in the deterioration in the coastal environment. In other words, marine pollution is causing the impoverishment of the population, resulting in a loss of 97.21 million euros in annual gross income or 5,190 euros per affected household.

Moreover, the analysis uncovers significant spatial dependence in terms of income distribution among neighboring territories. While being located at the Mar Menor's coast the seawater deterioration directly affected residents' income by -6.7%, the indirect impact was even more pronounced. Specifically, if a territory was situated on the Mar Menor coast and shared boundaries with other territories affected by the deteriorating seawater conditions, the income per capita experienced an additional decline of 11.4%.

In line with Larkin and Adams (2007), the economic consequences of in the deterioration in coastal environments can even surpass those caused by other environmental events. This agrees other findings that the seawater deterioration in the Mar Menor implied economic consequences in decreasing Airbnb accommodation prices (Fernández Ferrero et al., 2022), tourist arrivals (Mate-Sanchez-Val and Aparicio-Serrano, 2022) and firm' probability of survival (Maté Sánchez-Val and Aparicio-Serrano, 2023).

Our results underscore the necessity of implementing comprehensive policy measures to address both the environmental degradation and economic repercussions stemming from this issue. In addition to the proposed agricultural measures aimed at mitigating diffuse pollution (Alcon et al., 2022), other policy initiatives could include investing in sustainable agricultural practices, enforcing stricter regulations on pollutant discharge, promoting the restoration of natural habitats, and fostering social awareness campaigns on environmental conservation (IEO, 2020). Furthermore, targeted efforts should be made to enhance the income opportunities for local populations in affected coastal areas, such as through skills training programs, job creation initiatives, and support for small-scale sustainable enterprises. Collaborative efforts between national, regional, and local governmental bodies, as well as at the supranational EU level, are essential to effectively address the interconnected challenges posed by environmental degradation and its socio-economic impacts.

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Table 1. Descriptive statistics.

	Full sample		Treatment Group		Control Group	
Observations	1,914		48		1,866	
	Mean	SD	Mean	SD.	Mean	SD
Income	9.384	0.272	9.288	0.160	9.386	0.273
Foreign	11.184	11.96	26.400	14.96	10.793	9.964
Density	11.834	13.265	3.309	1.59	12.069	13.342
Gini	3.412	0.117	3.522	0.11	3.409	0.115
Working	66.510	6.028	66.240	6.892	66.520	6.006
Unemployment	7.512	2.267	7.163	2.474	7.521	2.194

Note: the table shows the mean and standard deviation (SD) for the complete sample, the treatment group, and the control group.

Table 2. Global Moran's index of dependent and explanatory variables in different spatial weighting matrices

variable	$k = 1$	$k = 2$	$k = 3$	$k = 4$
Income	27.767*** (0.000)	37.220*** (0.000)	44.592*** (0.000)	50.098*** (0.000)
Foreign	12.088*** (0.000)	14.075*** (0.000)	17.136*** (0.000)	19.567*** (0.000)
Density	23.575*** (0.000)	29.686*** (0.000)	34.620*** (0.000)	38.330*** (0.000)
Gini	19.475*** (0.000)	24.951*** (0.000)	29.896*** (0.000)	33.043*** (0.000)
Working	4.951*** (0.000)	6.211*** (0.000)	7.844*** (0.000)	8.177*** (0.000)
Unemployment	23.258*** (0.000)	30.758*** (0.000)	36.609*** (0.000)	41.252*** (0.000)

Note: *p<0.10; **p<0.05; ***p<0.01 indicate statistical significance at the 10%, 5% and 1%, respectively; p-values in brackets. For the weighted matrix specification, we employ the k-nearest neighbours' approach with k values ranging from 1 to 4.

Table 3. Baseline regression results for DID and SDID

	DID	SDID
	Log income	Log income
Time	0.092*** (0.000)	0.024*** (0.000)
Treat	-0.027 (0.476)	0.032 (0.207)
Time*Treat	-0.071 (0.177)	-0.058* (0.097)
Foreign	-0.007*** (0.000)	-0.004*** (0.000)
Density	0.031*** (0.000)	0.005*** (0.000)
Gini	0.914*** (0.000)	0.483*** (0.000)
Working	0.0001 (0.803)	0.001** (0.000)
Unemployment	-0.065*** (0.000)	-0.049*** (0.000)
Lag. foreign		-0.000** (0.057)
Lag. density		0.014*** (0.000)
Lag. Gini		0.024 (0.614)
Lag. working		-0.003*** (0.000)
Lag. unemployment		0.023*** (0.000)
Constant	6.743*** (0.000)	1.741*** (0.000)
Rho		0.675*** (0.000)
Adjusted R-squared	0.553	
AIC		-2401.800
Jarque Bera test in error terms		

Note: *p<0.10; **p<0.05; ***p<0.01 indicate statistical significance at the 10%, 5% and 1%, respectively; p-values in brackets. W is based on the k-closest neighbours. We consider k=4 closest neighbours to each census area. Our results were significant under changes in the k values. The estimates were calculated using the maximum likelihood estimation method.

Table 4. Test statistics for spatial dependence

	DID	SDID
LMlag	1307.300*** (0.000)	
LMerr	1164.800*** (0.000)	
RLMlag	261.730*** (0.000)	
RLMerr	119.180*** (0.000)	
LR Test (OLS-SDM)		1201.400*** (0.000)
LR Test (SAR-SDM)		127.330*** (0.000)
LR Test (SEM-SDM)		241.55*** (0.000)

Note: *p<0.10; **p<0.05; ***p<0.01 indicate statistical significance at the 10%, 5% and 1%; p-values in brackets. W is based on the k-closest neighbours. We consider k=4 closest neighbours to each census area. Our results were significant under changes in the k values.

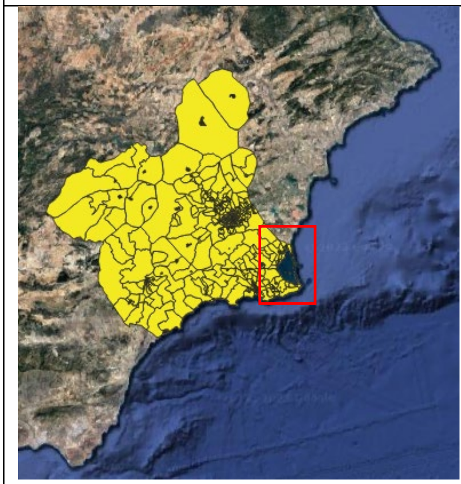
Table 5. Marginal effects

	Direct	Indirect	Total
Time	0.039*** (0.000)	0.066*** (0.000)	0.106*** (0.000)
Treat	0.037 (0.396)	0.063 (0.399)	0.101 (0.397)
Time*Treat	-0.067* (0.067)	-0.114* (0.068)	-0.181* (0.067)
Foreign	-0.005*** (0.000)	-0.010*** (0.000)	-0.015*** (0.000)
Density	0.008*** (0.000)	0.035*** (0.000)	0.043*** (0.000)
Gini	0.514*** (0.000)	0.931*** (0.000)	1.445*** (0.000)
Working	0.001 (0.270)	-0.005*** (0.001)	-0.004** (0.029)
Unemployment	-0.051*** (0.000)	-0.027*** (0.000)	-0.079*** (0.000)

Note: *$p<0.10$; **$p<0.05$; ***$p<0.01$ indicate statistical significance at the 10%, 5% and 1%. p-values in brackets.

Figure 1. Location of the Mar Menor coastal lagoon

a. Map of Spain (peninsula). Map drawn by census sections.

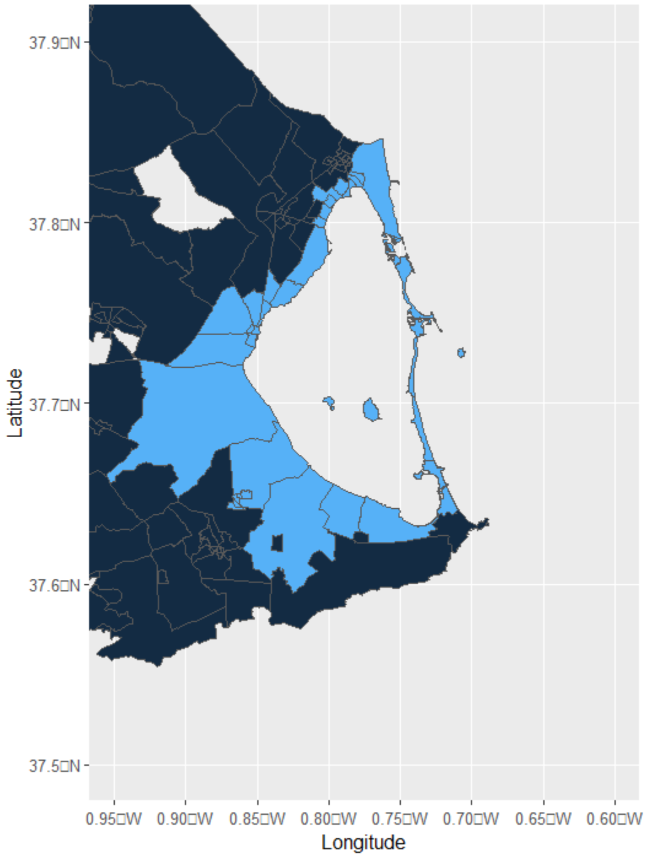


b. Location of study area, Region of Murcia, by census sections.

c. The Mar Menor coastal lagoon. Satellite image of Sentinel 2, date of the image: 2016-08-09

Source: Authors' own elaboration using QGIS Desktop version 3.18.1 (a, b) and SNAP 8.0 (c).

Figure 2. Map of the Mar Menor coastal area with census section administrative division. The treatment and control groups are coloured in light blue and dark blue, respectively.



Source: Authors' own elaboration using RStudio version 2023.06.0.

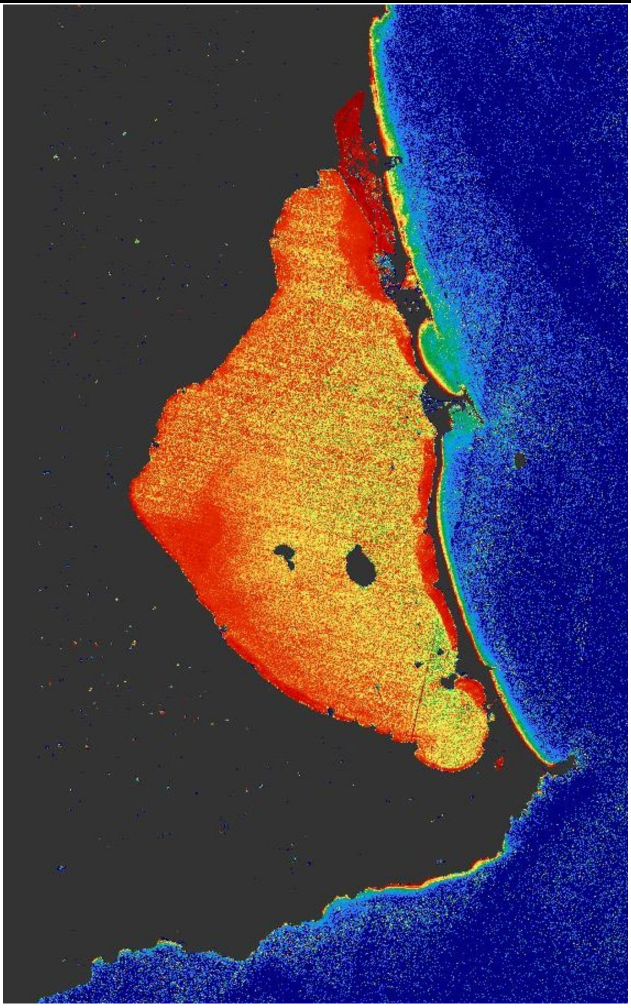
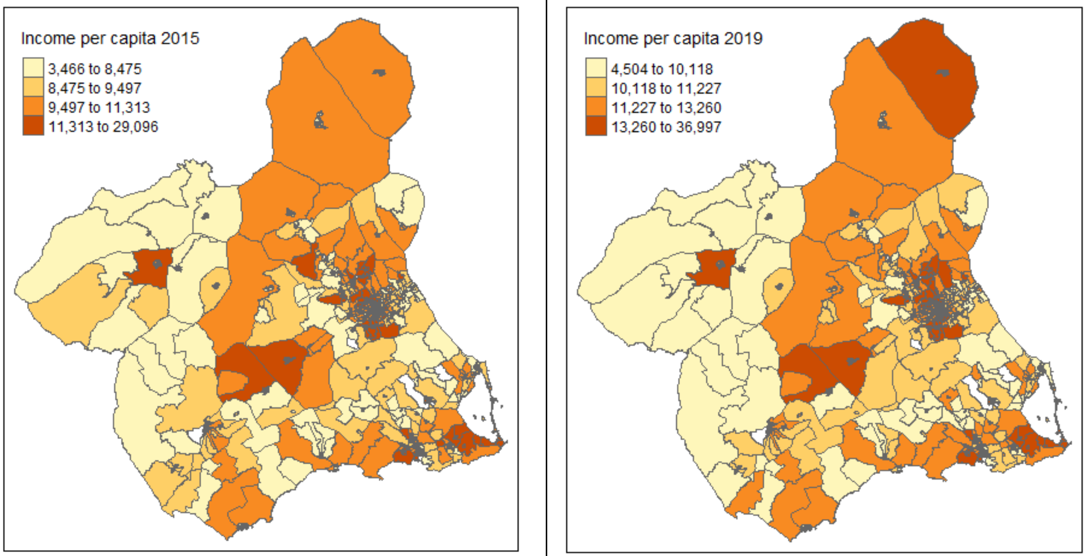
Figure 3. Chlorophyll concentration map in the Mar Menor

Source: Authors' construction. Note: The Chlorophyll Concentration Maps of the Mediterranean Spanish coast is drawn by Ocean and Land Colour Instrument (OLCI) processing tool from ESA with SNAP 8.0. Date of the image: 2016/08/07.

Figure 4. Map of the Region de Murcia at a census section administrative division. Income per capita by quartiles in the Region of Murcia.



Source: Authors' own elaboration with RStudio version 2023.06.0.