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Red tides decrease time use at social infrastructure places

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E-mail: haoluan.wang@miami.edu**Keywords:** harmful algal bloom, red tide, social infrastructure place, time use, environmental hazard, economic lossSupplementary material for this article is available [online](#)RECEIVED
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citation and DOI.**Abstract**

Harmful algal blooms (HABs) are intensifying globally, with well-documented ecological and health consequences. Yet their socioeconomic dimensions remain largely unexplored. Here, we quantify how red tides, a specific type of HABs, disrupt urban mobility and local commerce in coastal regions. Leveraging high-frequency mobile device data, we construct a tract-by-week panel for Florida's coastal counties (2019–2023) and apply fixed-effects models to estimate the effects of algae cell concentrations on visits and time spent at social infrastructure places. A one-million-cells-per-liter increase reduces time spent by 0.7%–1.1% and visits by 0.8%–0.9%, with stronger impacts during summer and at high algae cell concentration thresholds. These behavioral shifts translate into economic losses of US\$0.9–1.2 million for dining and grocery activities in 2023 alone. Our findings reveal that red tides impose substantial social and economic costs, underscoring the need for adaptation strategies in response to rising environmental hazards to protect vulnerable coastal communities.

1. Introduction

In recent decades, harmful algal blooms (HABs) have increased in frequency, spatial extent, and duration worldwide, driven by nutrient enrichment and invasive species (Glibert *et al* 2014, Glibert 2020, Gobler 2020). The United States has been a major locus of this trend, experiencing HABs caused by a wide range of bloom-forming species (Anderson *et al* 2021). Among them, *Karenia brevis* or red tides, is particularly damaging, producing toxins that pose severe risks to public health and generate substantial socioeconomic losses (Fleming *et al* 2011). Prior studies document that HAB exposure increases outpatient visits and healthcare costs (Bechard and Lang 2024), induces psychological distress among coastal residents (Grattan *et al* 2016), and is associated with population decline and a reduced share of children in affected areas (Chen and Wang 2025). HABs also disrupt coastal economies by reducing fishing trips (Jayasekera *et al* 2024), lowering fishing license sales (Wolf *et al* 2017), and triggering repeated

harvest season closures (Weir *et al* 2022). Beyond recreation and fisheries, elevated algal concentrations depress nearby property values (Bechard 2021, Wolf *et al* 2022) and increase homeowners' investments in residential infrastructure as a form of adaptation (Georgic *et al* 2025).

At the same time, the rapid growth of large-scale mobility datasets, particularly mobile phone trajectory data, has transformed the study of human activity and movement patterns (Gonzalez *et al* 2008, Song *et al* 2010). A growing body of research shows that mobility behavior is closely linked to socioeconomic status (Xu *et al* 2018) and shaped by local infrastructure, public services, and spatial planning (Barbosa *et al* 2021). Mobility responses are especially sensitive to shocks, including epidemic outbreaks, which alter daily routines and community-level interactions (Mendolia *et al* 2021, Coleman *et al* 2022). Environmental hazards likewise disrupt mobility patterns: hurricanes exacerbate inequalities in movement and slow post-disaster recovery (Hong *et al* 2021, He *et al* 2024), while air quality shocks such as

ozone exceedances and wildfire smoke reduce visitation to national parks and recreational sites (Keiser *et al* 2018, Gellman *et al* 2022).

Beyond measuring aggregate movement, mobility data also provide a powerful lens for examining how people allocate time across social infrastructure places, including leisure facilities, cafés, cultural venues, and religious spaces, settings that generate important social, psychological, and economic benefits. Existing research shows that access to commercial amenities and transportation hubs increases participation in shopping and leisure activities (Fan and Khattak 2009, Liu *et al* 2020). Eating and drinking establishments, such as cafés, are associated with psychological well-being (Lee 2022), while arts participation fosters social belonging through shared and collective experiences (Perkins *et al* 2021). Similarly, engagement in religious activities is linked to stronger social connectedness relative to nonparticipation (Hastings 2016). Despite these insights, relatively little is known about how environmental hazards reshape engagement with social infrastructure in everyday life, representing an important gap in the literature.

This study addresses that gap by leveraging high-frequency mobility data to examine how red tides influence human engagement with social infrastructure places. Using 43 089 recorded red tide events across 35 Florida coastal counties from 2019 to 2023, we construct a tract-by-week panel dataset ($N = 840,842$) and apply fixed-effects models to estimate the effects of algae cell concentration on visits to, and time spent at, social infrastructure locations. Our empirical strategy controls for local weather conditions, spatial fixed effects, and seasonality, allowing us to isolate spatiotemporal variation in red tide intensity. We find that elevated algae cell concentrations significantly reduce community-level social and economic activity, with heterogeneous effects across seasons and activity types, resulting in substantial localized economic losses. By providing granular, behavioral evidence of how red tides erode social interaction and everyday economic engagement, this study contributes to the literature on environmental hazards, human mobility, and social infrastructure. Our findings highlight the need for integrated monitoring, early-warning systems, and adaptation strategies to enhance the resilience of vulnerable coastal socio-ecological systems to growing environmental hazards.

2. Data and methods

2.1. Harmful algae cell concentration

We obtained geo-referenced red tide event data for 2019–2023 from the Florida Fish and Wildlife Conservation Commission (FWC). Each event records the sampling date, geographic coordinates (latitude and longitude), and the concentration of

Karenia brevis (the toxic algal species responsible for red tides) reported in cells per liter. Supplementary figure S1 shows the spatial distribution of red tide events during our study period by year.

Data processing involved several steps. First, in our analysis, a red tide event was defined as a monitoring observation with non-zero harmful algae cell concentration. Accordingly, monitoring observations with zero harmful algae cell counts were excluded from the raw dataset prior to aggregation. Second, because most monitoring sites were located in nearshore waters, we restricted our analysis to 35 coastal Florida counties, including Hernando, Wakulla, Walton, Volusia, Broward, Palm Beach, Miami-Dade, Citrus, St. Johns, Manatee, Pinellas, Franklin, Pasco, Duval, Martin, Dixie, Escambia, Monroe, Flagler, Lee, Bay, Jefferson, Levy, St. Lucie, Okaloosa, Collier, Sarasota, Taylor, Nassau, Santa Rosa, Brevard, Indian River, Gulf, Hillsborough, and Charlotte. For each census tract in these counties, we used the centroid to create a 2 mile buffer and then retained all red tide events within that buffer. As robustness checks, we varied the buffer radius to 1 mile and 3 miles. Finally, we aggregated all red tide events to the tract-by-week level and computed both the average and total cell concentration (million per liter). The average cell concentration was calculated as the mean concentration across all detected red tide events within each tract-week buffer, representing the typical exposure level during a given week. The total cell concentration was calculated as the sum of cell concentrations across detected red tide events within the tract-week buffer, intended to capture the combined intensity and persistence of bloom exposure over the week. We use both measures because our analysis focuses on tract-level exposure rather than bloom dynamics at individual monitoring points or offshore regions. Supplementary figures S2 and S3 show the spatial distribution of average and total cell concentration during our study period.

We note that excluding monitoring observations with zero harmful algae cell counts does not imply that census tracts or tract-weeks with zero red tide exposure were removed from the final panel dataset. Census tracts and weeks without detected red tide events were retained and assigned zero exposure values. In addition, the average cell concentration measure reflects bloom intensity conditional on detected red tide events rather than the average across all monitoring observations. While this distinction does not affect the total cell concentration measure, it may affect the interpretation of average cell concentration. As additional robustness checks, we recalculated average cell concentration using all monitoring observations, including zero cell-count records. We also expanded the sample to include all census tracts in Florida, assigning zero red tide exposure to inland tracts without observed red tide events.

2.2. Social-infrastructure time use (STU)

We obtained the STU data from Wang and Guo (2025). To measure the duration and intensity of time spent at social infrastructure places, the authors derived weekly STU patterns from Advan Weekly Patterns data. This dataset, based on 32 million devices across the U.S. (approximately 15% of U.S. phone users), captures weekly visit information for each point of interest. However, these data do not constitute a random sample of the population, as the records are derived from smartphone applications with location-sharing services enabled. Wang and Guo (2025) also note that the mobile device panel is dynamic and may vary across time and space, and the visitation measures are normalized by neighborhood panel size to reduce the influence of changing sampling rates. Similar smartphone mobility datasets derived from commercial location data providers have been widely used in interdisciplinary research on human mobility, public health, and social behavior (Jay *et al* 2020, Chang *et al* 2021). The aggregated data, ranging from census tracts to metropolitan areas, include both the total number of visits and the total visit time (minutes). Additionally, the dataset provides the total number of visits across various categories of social infrastructure, including arts, consumer services, dining, grocery, religious venues, and sports (supplementary table S1 provides descriptions). For this study, we used weekly data for 2019–2023 at the census tract level, aligned to the 2019 census tract boundaries, and matched them to the harmful algae cell concentration data. Supplementary figures S4 and S5 show the spatial distribution of the number of visits and total visit time at the tract-by-week level during our study period by year.

2.3. Weather variables

The gridMET dataset from the Climatology Lab provides daily, high-resolution weather data (1/24° arc-degree, approximately 4 km) from 1979 to the present (Abatzoglou 2013). For this study, we selected key weather variables, including minimum air temperature (°C), maximum air temperature (°C), precipitation (mm), wind speed (m s^{-1}), and relative humidity (%). Daily observations were aggregated to the weekly level based on the STU dataset's week definitions, and mean values for each variable were computed for every census tract included in the analysis.

2.4. Census tract variables

To further investigate the socio-demographic characteristics associated with the census tracts in this study, we selected several variables from the American Community Survey 5 Year-Estimates 2015–2019 (aligned to the 2019 census tract boundaries), including total population, age groups (0–18, 18–34, 35–64, and over 65 years old), race and ethnicity (White,

Black, Asian, and Hispanic populations), and median household income.

2.5. Empirical model

To estimate the impact of harmful algae cell concentration on time use at social infrastructure places, we use an econometric regression model as follows:

$$\ln(\text{STU}_{ijkt}) = \beta \text{HAB}_{ijkt} + \gamma X_{ijkt} + f_{ijkt} + \varepsilon_{ijkt} \quad (1)$$

where $\ln(\text{STU}_{ijkt})$ is the natural logarithm of the dependent variable for census tract i in county j during week k of year t . For the dependent variable, we use both the total time (minutes) spent at social infrastructure places and the number of visits to these places. Due to the skewed distribution of these two variables, we apply the natural logarithm transformation. Therefore, the estimated coefficients are interpreted as the impact on the percentage change in the total time or the number of visits. Our key explanatory variable, HAB_{ijkt} , captures the harmful algae cell concentration in either the average or total cell concentration (millions per liter). Additionally, we include a vector of weather controls X_{ijkt} including the average temperature (°C), precipitation (mm), wind speed (m s^{-1}), and relative humidity (%).

To account for unobserved heterogeneity across regions and time periods, we follow a high-dimensional fixed-effects framework that is widely used in panel data analysis (Guimaraes and Portugal 2010, Wooldridge 2010) and incorporate, f_{ijkt} , a suite of fixed effects with varying combinations into the model. Specifically, census tract fixed effects control for time-invariant characteristics of tracts that may influence both red tide exposure and time spent at social infrastructure locations, such as local infrastructure or socio-economic conditions. Temporal fixed effects, including week-of-year, month, and year, capture time-related variations that affect patterns of time use, such as seasonality, holidays, or long-term trends. Finally, interaction fixed effects, such as county-by-month and county-by-year, account for region-specific temporal trends. The inclusion of interaction fixed effects also helps account for shocks affecting mobility behavior during the COVID-19 pandemic. Particularly, month-by-year fixed effects absorb statewide shocks that vary over calendar time, such as lockdown periods, reopening phases, pandemic waves, and other statewide mobility disruptions. County-by-year fixed effects further account for county-level annual shocks and heterogeneous local recovery patterns during and after the pandemic.

For robustness checks, we use four sets of fixed effects, including (1) census tract, week, month, and year fixed effects; (2) census tract, week, month-by-year fixed effects; (3) census tract, week, month, and county-by-year fixed effects; and (4) census tract, week, year, and county-by-month fixed effects. These

specifications allow us to control for regional and temporal heterogeneity in multiple ways, enhancing the precision and robustness of our estimates of red tides' impact on time spent at social infrastructure locations.

We cluster standard errors in two ways to address potential spatial and temporal correlation. First, we cluster at the tract level to capture correlations within the same geographic area. Second, we cluster at the tract-by-week level to account for correlations over time within each tract. This dual clustering approach strengthens inference by mitigating concerns about serial correlation and spatial dependence in the error terms.

To investigate whether different levels of algae cell concentration have differential effects on time use at social infrastructure places, we use the econometric regression model as follows:

$$\ln(STU_{ijkt}) = \beta_1 HAB_{ijkt}^1 + \beta_2 HAB_{ijkt}^2 + \beta_3 HAB_{ijkt}^3 + \beta_4 HAB_{ijkt}^4 + \beta_5 HAB_{ijkt}^5 + \gamma X_{ijkt} + f_{ijkt} + \varepsilon_{ijkt} \quad (2)$$

where HAB_{ijkt}^1 , HAB_{ijkt}^2 , HAB_{ijkt}^3 , HAB_{ijkt}^4 , and HAB_{ijkt}^5 are dummy variables respectively indicating whether the algae cell concentration for census tract i in county j during week k of year t is categorized as background (1–1000), very low (1000–10 000), low (10000–100 000), medium (100 000–100 0000), and high (>100 0000) according to FWC. Zero cell concentration serves as the baseline in the model. Again, both average and total cell concentration are used. For simplicity, we choose our preferred model specification (tract, week, and month-by-year fixed effects with standard errors clustered at the tract-by-week level) for this analysis. All other variables remain the same as specified in equation (1).

To estimate the dynamic effects of red tide exposure, we use the econometric regression model as follows:

$$\ln(STU_{ijkt}) = \sum_{t=-3}^{t=3} \beta^t HAB_{ijkt} + \gamma X_{ijkt} + f_{ijkt} + \varepsilon_{ijkt} \quad (3)$$

where we incorporate the current cell concentration along with up to three lead and lag weeks, with values from -1 to -3 representing previous one to three weeks and values from 1 to 3 representing one to three weeks in the future. Lagged terms are included to examine whether the behavioral effects of red tide exposure persist over time, while lead terms serve as a placebo and diagnostic test for potential anticipatory responses or pre-existing temporal trends. For simplicity, we choose our preferred model specification (tract, week, and month-by-year fixed effects with standard errors clustered at the tract-by-week level) for this analysis. All other variables remain the same as specified in equation (1).

3. Results

3.1. Trends in time use at social infrastructure places and harmful algae cell concentration

Figure 1 shows seasonal trends in time use at social infrastructure places and harmful algae cell concentrations at the census tract level from 2019–2023 (summary statistics in supplementary table S2). Time use follows a clear disruption-and-recovery pattern (figure 1(a)). In 2019, the annual average visit time was high (98 310 min) with minimal seasonal variation. In 2020, COVID-19 triggered a sharp decline starting in spring, dropping the annual average to 62 820 min. Recovery began in 2021–2022 (67 757 and 78 119 min), though winter lows became pronounced. By 2023, the average reached 81 608 min, still below 2019, and declined again in the fall. Visit counts mirror this trend (figure 1(b)). A steep fall in 2020, a gradual rebound in 2021–2022, and winter dips post-pandemic. In 2023, annual visits rose to 2245, surpassing 2019 levels. The trends for average and total cell concentrations (figures 1(c) and (d)) are nearly identical across years, with evident seasonal variation. Red tide activity was lowest in 2020, with tract-level annual averages of 1061 and 1939 cells per liter. The most severe year was 2021, when averages surged to 0.015 and 0.055 million cells per liter, peaking sharply in summer. In 2019 and 2022, outbreaks mainly occurred in late fall, whereas in 2023, the primary peak shifted to winter.

3.2. Higher harmful algae cell concentration decreases number of visits and total visit time

We examine how red tide exposure influences time spent at social infrastructure locations using econometric regression models that incorporate various combinations of fixed effects and clustered standard errors. Red tide exposure is measured in two ways: average cell concentration and total cell concentration. We analyze two outcomes: the number of visits and the total visit time.

Figure 2(a) shows that a one-million cells per liter increase in average cell concentration reduces the total time spent at these locations by approximately 0.7% ($P < 0.01$) to 1.1% ($P < 0.001$). Total cell concentration shows a similar trend, though with smaller effect sizes and lower statistical significance (figure 2(b)). Likewise, figure 2(c) demonstrates that a one-million cells per liter in average cell concentration decreases the total number of visits by about 0.8% ($P < 0.001$) to 0.9% ($P < 0.001$), while total cell concentration again exhibits a comparable but weaker effect (figure 2(d)). Supplementary information shows that our results are robust when the sample is restricted to census tracts ever exposed to red tides (figure S6), when average cell concentration is recalculated using all monitoring observations, including zero cell-count records (figure S7), when all census tracts in Florida are included in the analysis (figure

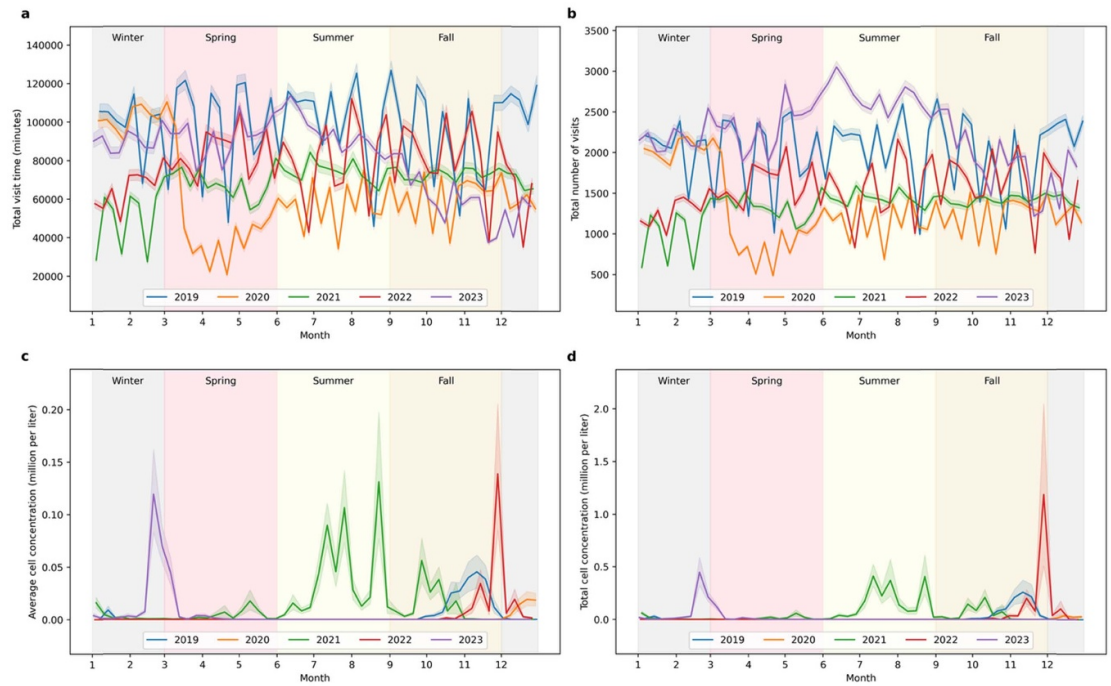


Figure 1. Trends in time use at social infrastructure places and harmful algae cell concentration (2019–2023). (a), Total visit time at social infrastructure places (minutes). (b), Total number of visits. (c), Average harmful algae cell concentration (million per liter). (d), Total harmful algae cell concentration (million per liter). Lines represent tract-week averages for each calendar year (2019–2023), with colors distinguishing the years. The background shading indicates the four seasons, including winter (December–February), spring (March–May), summer (June–August), and fall (September–November).

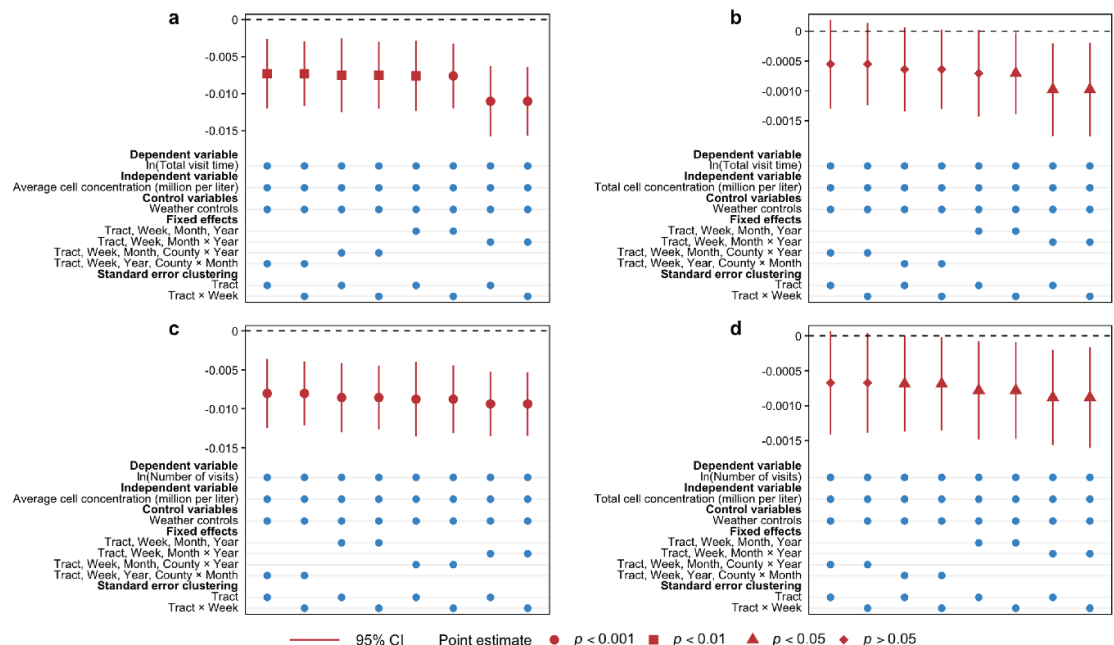
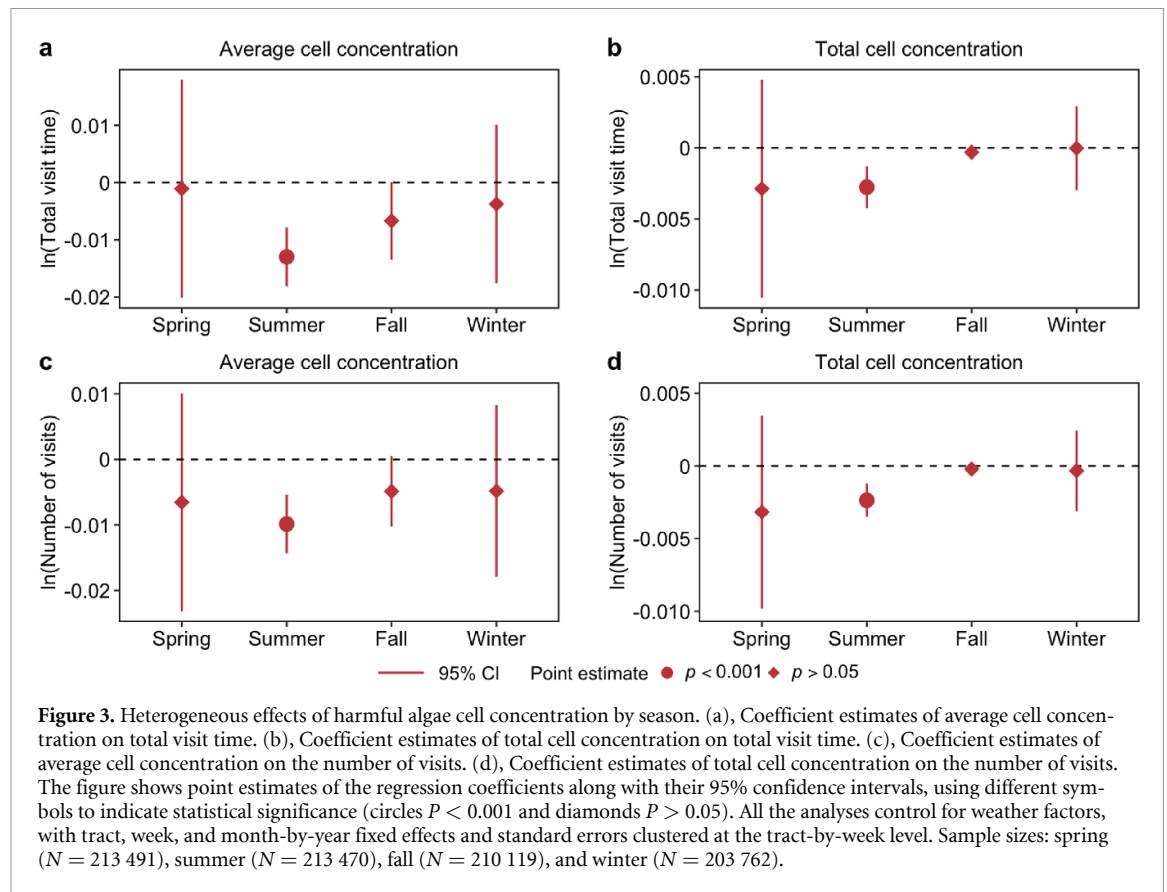


Figure 2. Effects of harmful algae cell concentration on time use at social infrastructure places. (a), Coefficient estimates of average cell concentration on total visit time. (b), Coefficient estimates of total cell concentration on total visit time. (c), Coefficient estimates of average cell concentration on the number of visits. (d), Coefficient estimates of total cell concentration on the number of visits. Each panel consists of two sections. The upper section shows point estimates of the regression coefficients along with their 95% confidence intervals, using different symbols to indicate statistical significance (circles $P < 0.001$, squares $P < 0.01$, triangles $P < 0.05$, and diamonds $P > 0.05$). The lower section summarizes the model specifications, including the dependent and independent variables, control variables, fixed effects, and the clustering approach for standard errors. Sample size: $N = 840\,842$.



S8), when a 1 mile buffer (figure S9) or a 3 mile buffer (figure S10) is used to calculate red tide exposure, when the year 2020 is excluded due to the concern of COVID-19 (figure S11), and when previous and future weeks of red tide exposure are included in the model (figure S12).

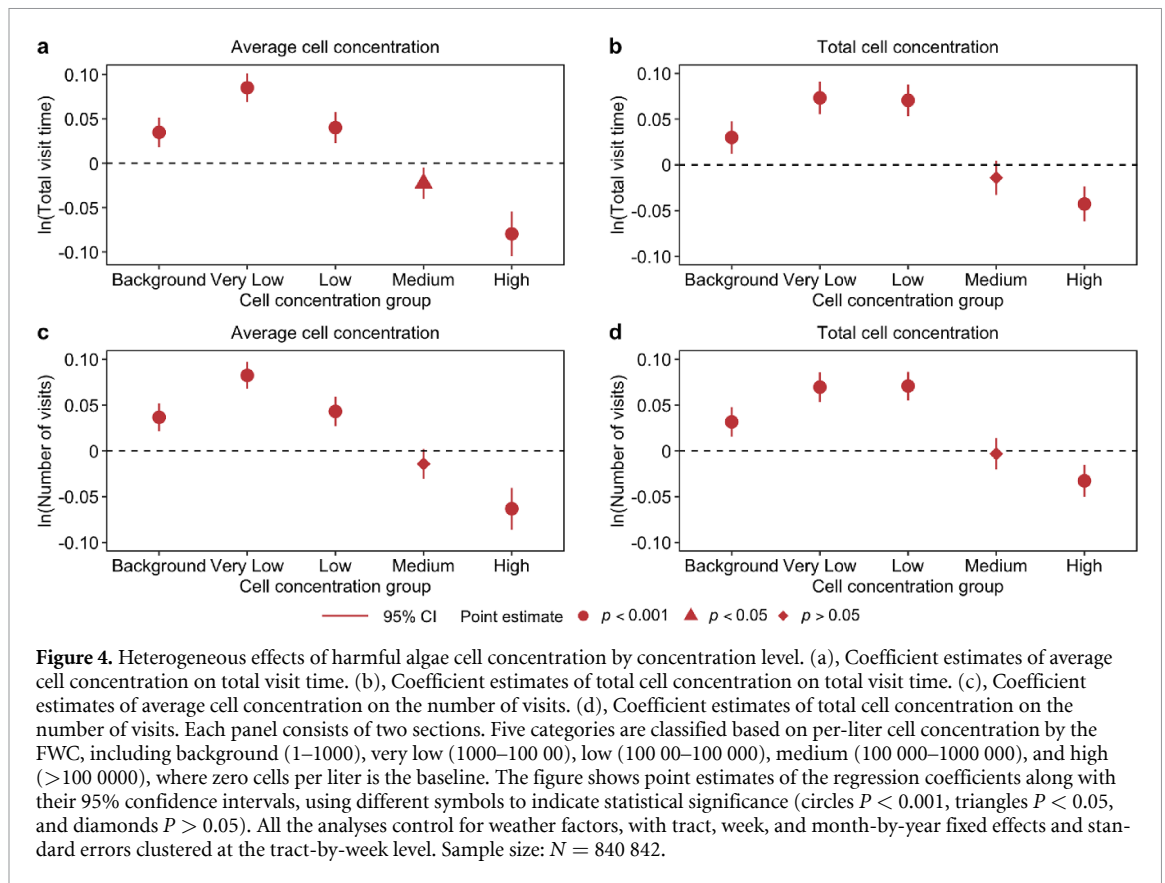
3.3. Largest effects occur during summer

Using our preferred model specification (tract, week, and month-by-year fixed effects with standard errors clustered at the tract-by-week level), we assess whether red tide exposure affects time use differently across seasons. As shown in figure 3, during our 2019–2023 study period, neither average nor total cell concentration significantly influences time use in spring, fall, or winter. In summer, however, the negative effect is most pronounced. A one-million cells per liter increase in average concentration reduces total visit time by 1.3% ($P < 0.001$) and the number of visits by 1.0% ($P < 0.001$). Similarly, an equivalent increase in total concentration decreases total visit time by 0.28% ($P < 0.001$) and visits by 0.24% ($P < 0.001$). We note, however, that this seasonal pattern may partly reflect the unusually severe and spatially extensive *Karenia brevis* blooms in summer 2021 (figure 1), whereas historical Florida red tide events have often peaked during fall seasons.

3.4. High algae cell concentration level is the main driver

We further examine how different harmful algae cell concentration levels affect time use at social infrastructure places (figure 4). Five categories are classified based on per-liter cell concentration by FWC, including background (1–1000), very low (1000–10 000), low (10000–100 000), medium (100 000–1000 000), and high (>100 0000), where zero cells per liter is the baseline. Results from our preferred model indicate that, relative to no cells, cell concentrations with background, very low, and low levels are associated with modest increases in time use. In contrast, medium and high cell concentrations reduce time use. For the high cell concentration, a one-million cells per liter increase in average concentration decreases total visit time by 8.0% ($P < 0.001$) and visits by 6.3% ($P < 0.001$). Similarly, an equivalent increase in total concentration lowers total visit time by 4.3% ($P < 0.001$) and visits by 3.3% ($P < 0.001$).

These concentration categories are also relevant for public communication and awareness. The FWC regularly communicates red tide conditions through a daily sample map, weekly statewide status reports, and a public hotline. These reports classify *Karenia brevis* abundance into categories ranging from background to high concentrations



and describe the possible effects associated with each level. According to FWC, medium and high concentrations are associated with more visible and publicly salient effects, including respiratory irritation, shellfish harvesting closures, fish kills, satellite detection, and water discoloration. Therefore, the stronger effects observed at higher concentration levels may reflect not only greater biological exposure intensity but also increased public awareness through agency updates, advisories, and media coverage.

3.5. Harmful algae cell concentration differentially impacts different activities

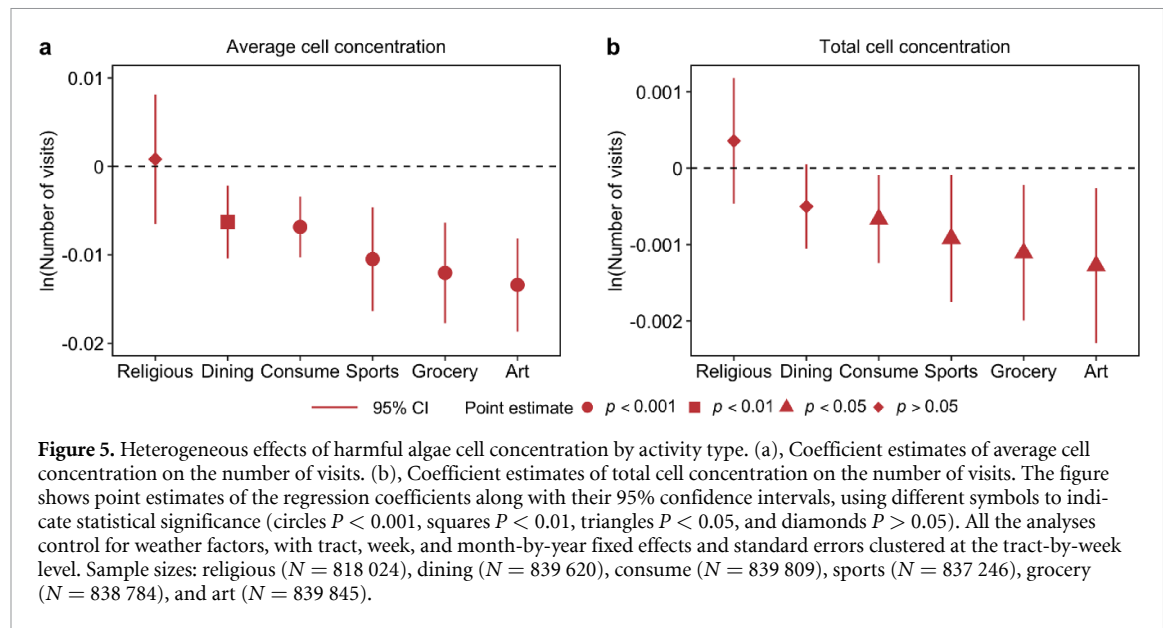
We also examine the heterogeneous effects of red tide exposure across different activity types, including religious, dining, consumption, sports, grocery, and art, using our preferred model (figure 5). Notably, the impact of cell concentrations on religious activities is not statistically significant. In contrast, the effects on other activities are consistently negative and statistically significant. Specifically, a one-million cells per liter increase in average cell concentration reduces the total number of visits by approximately 0.6% ($P = 0.003$) for dining, 0.7% ($P < 0.001$) for consumption, 1% ($P < 0.001$) for sports, 1.2% ($P < 0.001$) for grocery, and 1.3% ($P < 0.001$) for art. Similarly, a one-million cells per liter increase in total cell concentration decreases visits by about 0.05% ($P = 0.075$) for dining, 0.07% ($P = 0.023$) for consumption, 0.09% ($P = 0.030$) for sports, 0.11%

($P = 0.014$) for grocery, and 0.13% ($P = 0.014$) for art.

The null effect for religious activities provides a useful reference point for interpreting these heterogeneous responses. Religious visits may be less sensitive to red tide exposure because they are more likely to reflect routine local activities rather than discretionary or tourism-related behavior. By contrast, dining, sports, grocery, and arts activities may be more responsive to environmental conditions, tourism demand, and public awareness of red tide events. The relatively large reduction in arts-related visits may further reflect the discretionary and event-based nature of these activities, such as festivals, concerts, museums, and cultural venues, which may be particularly sensitive to changes in visitor flows, event attendance, and local conditions during red tide episodes. We also examined whether the effects of red tide exposure varied across census tracts with different socio-demographic characteristics, including population, age structure, race, and income levels. Detailed results are presented in supplementary figures S13 and S14.

3.6. Economic losses from reduced dining and grocery activities

We provide a back-of-the-envelope estimate of the economic loss from reduced dining and grocery activities attributable to red tide exposure. These estimates are intended to provide an approximate sense of



magnitude rather than a precise accounting measure of total economic damages. Our regression analysis indicates that a one-million-cells-per-liter increase in average algae concentration corresponds to approximately a 0.6% decline in dining visits and a 1.2% decline in grocery visits at the tract-by-week level. To translate these effects into monetary terms, we draw on industry-level consumption data from the 2023 U.S. Foods dining trends report and U.S. grocery shopper trends surveys. According to these sources, Americans spend an average of \$166 per person per month on dining out and dine out about three times monthly, implying roughly \$55.33 per visit. In 2023, U.S. households spent an average of \$164 per week on groceries and made about 1.6 shopping trips weekly, yielding an estimated \$102.50 per grocery visit.

In our data, let x_{it} and y_{it} denote the average algae concentration (in millions of cells per liter) and the number of dining visits in tract i during week t , respectively. Combining the average expenditure per person per dining visit and accounting for the fact that the mobility data we use in this study represents about 15% of U.S. phone users (Wang and Guo 2025), the implied reduction in dining-related expenditure for tract i in week t due to HABs is $\Delta E_{it}^{\text{Dining}} = \$55.33 \times 0.6\% \times \frac{1}{15\%} \times x_{it} \times y_{it}$. Aggregating these tract-by-week estimates across all 3260 coastal census tracts and 52 weeks in 2023 results in an estimated economic loss from reduced dining activity attributable to HABs in coastal Florida $E^{\text{Dining}} = \sum_{i=1}^{3260} \sum_{t=1}^{52} \Delta E_{it}^{\text{Dining}} \approx \$916003$. Figure 6(a) shows the weekly temporal trend of average tract-level estimates, and figure 6(c) shows the spatial distribution of total estimates across tracts.

Similarly, let x_{it} and y_{it} denote the average algae concentration (in millions of cells per liter) and the number of grocery visits in tract i during week t ,

respectively. Combining the average expenditure per grocery visit and accounting for the fact that the mobility data represents about 15% of U.S. phone users (Wang and Guo 2025), the implied reduction in grocery-related expenditure for tract i in week t due to HABs is $\Delta E_{it}^{\text{Grocery}} = \$102.5 \times 1.2\% \times \frac{1}{15\%} \times x_{it} \times y_{it}$. Aggregating these tract-by-week estimates across all 3260 coastal census tracts and 52 weeks in 2023 results in an estimated economic loss from reduced grocery activity attributable to HABs in coastal Florida $E^{\text{Grocery}} = \sum_{i=1}^{3260} \sum_{t=1}^{52} \Delta E_{it}^{\text{Grocery}} \approx \$1203090$. Figure 6(b) shows the weekly temporal trend of average tract-level estimates, and figure 6(d) shows the spatial distribution of total estimates across tracts.

4. Discussion and conclusions

The growing frequency and severity of different environmental hazards worldwide have disrupted human mobility and daily activities. Prior research highlights that national parks experience fewer visitation days when ozone concentrations exceed unhealthy levels (Keiser *et al* 2018); wildfire smoke reduces camper visits and increases campsite cancellations (Gellman *et al* 2022); and heavy air pollution discourages outdoor exercise (Fan 2024) and lowers movie ticket sales (He *et al* 2022). These declines in human activity impose substantial social costs, especially for the economy. We contribute to this body of evidence by showing that red tides, a growing coastal environmental hazard, significantly reduces time use at social infrastructure places.

The findings that higher concentrations of harmful algae cells reduce visits and shorten time spent at social infrastructure places, especially when the cell concentration level is high or during summer when

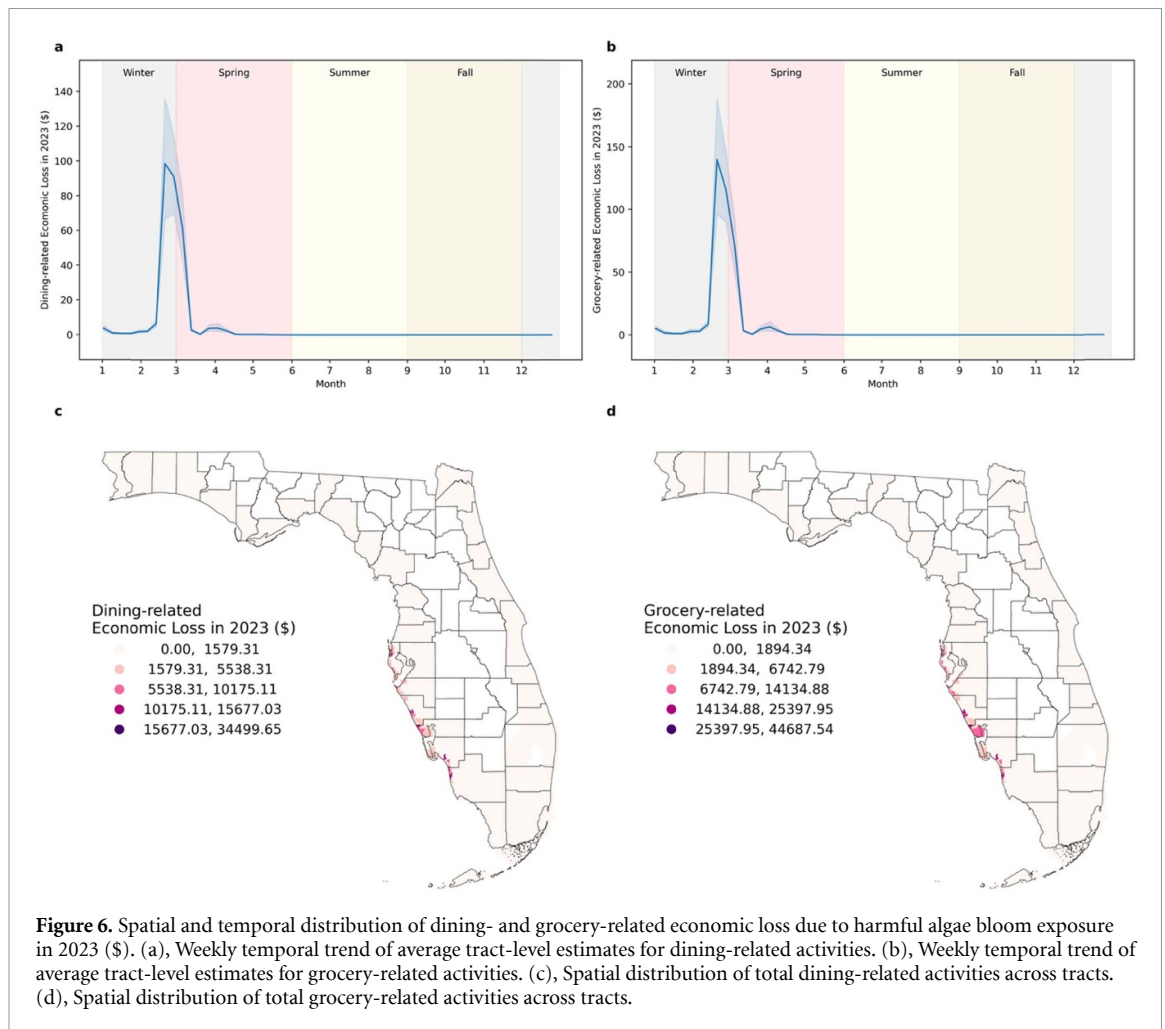


Figure 6. Spatial and temporal distribution of dining- and grocery-related economic loss due to harmful algae bloom exposure in 2023 (\$). (a), Weekly temporal trend of average tract-level estimates for dining-related activities. (b), Weekly temporal trend of average tract-level estimates for grocery-related activities. (c), Spatial distribution of total dining-related activities across tracts. (d), Spatial distribution of total grocery-related activities across tracts.

recreational demand peaks, carry urgent implications for building resilience in coastal socio-ecological systems amid increasing red tide threats. Enhanced investment in bloom forecasting, real-time monitoring, and early-warning systems could enable targeted, evidence-based advisories that minimize blanket restrictions and associated disruptions. Recent advances in *Karenia brevis* forecasting illustrate this potential. For example, Liu *et al* (2023) developed a short-term trajectory forecasting framework to predict the transport and movement of red tide blooms on the West Florida Shelf, while Medina *et al* (2024) developed an early-warning forecast model for red tide outbreaks along the southwest coast of Florida. Such predictive tools could help coastal communities, businesses, and public agencies respond more proactively to bloom events and reduce associated social and economic disruptions. More importantly, complementing technological advances, adaptive business strategies, such as flexible policies, incentive programs, or diversified offerings linking indoor alternatives, could mitigate short-term losses, especially in summer seasons when compounded heat further constrains household consumption (Lai *et al* 2022). Integrating such measures into coastal management frameworks would not only safeguard public health

and economies but also preserve vital social interactions that underpin community cohesion.

We acknowledge several limitations, and future research can build upon our study in multiple ways. First, our census-tract level aggregation may obscure finer-scale variation in red tide exposure (e.g. proximity to shorelines). Future studies could incorporate individual-level GPS or smartphone mobility data to capture finer spatial and behavioral patterns. Second, our time-use estimates rely on passive mobile-phone data derived from smartphone applications with location-sharing services enabled rather than from a random population sample. As a result, certain subpopulations, such as children, older adults, and low-income individuals without smartphones, may be underrepresented. Although similar mobile-phone-based mobility datasets have been widely used to capture aggregate behavioral patterns, potential representativeness biases may still remain. Combining these data with household travel surveys, wearable sensors, or other complementary data sources would help improve representativeness in future research. Third, our findings may not generalize beyond Florida's *Karenia brevis*-dominated red tides. Ecological drivers, toxins, and public awareness differ substantially from other HAB species. Whether

these patterns extend to freshwater systems or other marine HABs remains an open question.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: <https://github.com/UM-SER/HAB-STU>.

Supplementary information available at <https://doi.org/10.1088/1748-9326/ae80e6/data1>.

Data and code availability

The datasets used in this study are all publicly available. Data on the HAB events are available: <https://geodata.myfwc.com/maps/eecd72261da2412192123f5a96c4150c/about>. Data on the time use at social infrastructure places are available: <https://doi.org/10.1038/s41597-025-05504-9>. Data on weather variables are available: www.climatologylab.org/gridmet.html. Data on census tract variables are available: www.socialexplorer.com/. The raw and processed data used for all the analyses in this study are publicly available on the research team's GitHub repository: <https://github.com/UM-SER/HAB-STU>.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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