Abstract

Globally, drowning is the third leading cause of unintentional injury death, accounting for 7% of all injury-related deaths. This study aimed to examine the spatial clustering in UK drowning incidents. Data were obtained from the Water Incident Database (WAID) (1/1/2012–31/12/19). We examined spatial clustering of intentional and unintentional drownings using a density-based spatial clustering of applications with the noise method (DBSCAN). Intentional and unintentional events were delineated to establish thresholds for cluster identification for moderate, high and very high priority areas respectively, all within a 500-metre radius (i.e., 5-7 minute walk) of the water network. We identified 2 very high priority (*minPts* 8), 5 high priority (*minPts* 6) and 21 moderate priority (minimum points [*minPts*] 4) areas for unintentional drowning. This study also identified 4 very high priority (*minPts* 16), 16 high priority (*minPts* 8) and 36 moderate priority (*minPts* 4) areas for intentional drownings. Our findings serve to identify priority spatial locations, which provide important foundations for drowning prevention interventions. Prevention efforts should now consider the wider determinants of drowning in these areas, including accounting for the evident spatial patterns in drowning events. Our study addresses key priorities of United Nations and World Health Organisation's drowning prevention guidelines.

1. Introduction

Globally, drowning is the 3rd leading cause of unintentional injury death, accounting for 7% of all injury-related deaths[1]. Worldwide estimates suggest that drowning claimed more than 2.5 million lives between 2008 and 2018; deaths which were largely preventable[2]. Such events are not restricted to adults with drowning listed among the top ten causes of death for young people in every region of the world[3]. These statistics probably represent a significant underestimation, potentially by as much as four or five times[4, 5] because many countries, particularly those classified as lower or middle income, have limited or non-existent mechanisms to document drowning or fail to distinguish death as a result of drowning[4, 5]. High-income countries also suffer high drowning rates with an average of ~1.43 drownings per 100,000 of the population across Australia, Canada and New Zealand[6]. In the United Kingdom, death by drowning is also a significant cause of intentional and unintentional death with an average of 631 deaths recorded between 2012 and 2019 (~0.97 deaths per 100,000 population[7]). While drowning has an individual, societal and moral burden, recent estimates from the United Kingdom suggest a significant economic cost with approximately £139.2 million GBP spent annually on running the rescue response to drowning and water-based incidents[8]. The onward cost of medical care, morbidities and co-morbidities associated with fatal and non-fatal drownings will contribute further to this figure[9]. Indeed, drowning has other significant impacts, including loss of household income and support, family breakdown and increased burden of care for survivors [10].

Clearly, it is in the societal interest to establish the leading risk factors for drowning and an appropriate evidence base to reduce drowning frequency[11]. One obstacle to achieving this is that drowning is a multifaceted phenomenon that is not easily addressed by a single solution[12]. Several factors, which include individual, family, community, economic and structural variables (i.e., man-made and natural hazards) may relate to increased drowning incidence[12]. Most studies highlight that the risk of drowning is higher for males than females and young children than for other ages[1, 3]. More generally, families who undertake frequent water-related recreational activities whilst not utilising personal floatation devices are exposed to a higher drowning risk[13]. Other factors are context specific. For example, in the UK, low average annual water temperature is known to evoke the cold shock response involving loss of respiratory control and increased chance of aspirating water to the lung causing asphyxiation and drowning [7, 14].

Evidence from a seminal World Health Organisation (WHO) report[3] suggests that populations at elevated risk of drowning include those with lower socioeconomic status such as poorer levels of education, people living in rural and remote settings and ethnic-minority populations both in high-income and low-income countries[3]. Whilst evidence for these factors as contributors to drownings has been presented, it remains difficult to separate their contribution to specific drowning outcomes or high priority locations owing to their nuanced influence on drowning risk. It is a more logistically feasible exercise to first identify the geospatial distribution of drownings, identify high priority areas based on fatal drowning data, and then backward extrapolate the characteristics that may have contributed at an individual, environmental and socioeconomic level. The first step in this sequence of epidemiological investigation is to use geospatial methods to describe drowning distribution and identify hotspots where drownings occur more frequently, which has seldom been carried out internationally and represents a new area of health geography research and spatial epidemiology.

Intervening at the population-level using a multi-faceted strategy such as a combination of individual, environmental and population-level interventions within a socio-ecological framework is increasingly considered an effective approach for intervention[15-17]. Population-level interventions aim to improve the health of an entire population within and across a defined regional or national population. Such interventions can be extremely effective. For example, in a recent study mandatory regulations at a population-level increased lifejacket use by more than 50%, whilst the educational campaign increased lifejacket use by 2% and this small increase was unsustained over time[18]. While population-level interventions are important according to the behavioural epidemiological framework an important first step is to effectively measure the given behaviour prior to assessing correlates, determinants and assessing the effectiveness of interventions[19]. In the UK for instance, whilst we have a good overview of who is drowning[7] there has been little if any investigation into where such drownings are occurring and how these cluster in space. Therefore, according to the behavioural epidemiological framework prior to developing any interventions or investigating causative factors it is first important to measure the given behaviour, which includes in this case where drowning is occurring most so interventions can be effectively targeted to specific areas[19]. Once we know where drownings are occurring most then research can progress to investigating what factors may influence drowning incidence in these locations however, we first need to establish how often and where drownings may be occurring at a population-level [10, 17, 19].

The type of environments in which drownings occur have primarily been documented at a descriptive level[20]. Fewer studies have examined drowning incidence using Geographic Information Systems (GIS). While geospatial methods have a long history of use in public health their application to injury data, including drowning incidence, are still relatively novel and underutilised[21]. Within spatial and spatio-temporal epidemiology, the application of geospatial methods has been recognised as important to gain a greater understanding of the complex nature of the injury and the associated range of geographically diverse risk factors[21]. Further research is needed to account for the interplay between environmental risk factors in relation to their spatial distribution. A review has highlighted a lack of evidence in the field of unintentional injury research that has used geospatial or spatial clustering techniques[21]. In one of only a few studies to have done so, evidence from the state of Georgia, USA[22] showed substantial spatial variation in drowning density and rate with high-density drowning neighbourhoods identified as having a significantly lower rank of median income and lower rank of educational attainment. Moreover, Geographically Weighted Regression analysis demonstrated how such associations varied over space[22]. Another more recent paper examining drowning data at a national level (in Spain) showed a significant relationship between accidental drowning and meteorological variables during summer months in the study period between 1999 and 2018[23]. In addition, drowning deaths were spatially correlated with sea-level pressure over the Mediterranean basin highlighting the important role of the wider determinants of drowning risk[23]. Even less attention has been placed on intentional drownings, yet it is likely that, similar to data from comparative unintentional and intentional studies, the victim profile and therefore risk factors, will be different[24, 25]. Hence the geo-spatial characteristics of the surrounding environments relating to intentional versus unintentional drownings may also be different.

Despite the WHO publishing clear guidance on implementing a drowning prevention framework[11], few countries have validated their processes against this guide. The WHO implementation guide[11] for drowning prevention research highlighted the value of research that focuses on improving understanding of drowning data. In addition to this, the UN resolution on global drowning prevention[2] also outlined the need for innovative data driven approaches to inform multisector solutions in drowning prevention. Having already commenced this approach and verified that the data quality of the UK's drowning database meets the WHO requirements[7], we are now able to respond to calls from WHO and UN to address the next steps of the guide – to identify epidemiological patterns and risk factors. Our approach responds to calls from WHO and UN guidelines, which stipulate a series of sequential stages, beginning with analysing existing data and outlining the nature and scale of the problem, before assessing risk factors and developing targeted interventions. Whilst risk factors at the "host" (i.e., individual age and sex characteristics) level have been extensively investigated[6, 26], studies of environmental risk factors at key locations are sparse. This may be a result of few databases habitually documenting drowning location using high spatial resolution data such as coordinates (e.g., latitude and longitude) that would enable such an analysis to be conducted. Where geographic location data are included, they typically describe the location using a categorical approach by type of location as opposed to using co-ordinates[6]. Such an approach limits the methods available to improve the effectiveness of drowning interventions by identifying specific drowning locations or clusters of high priority environments[27]. Critically, the UK data include specific geographic coordinates of each fatal drowning event thereby expanding the available methods for research.

Accordingly, to reduce drowning incidence worldwide, and in the UK, a better understanding of the wider factors that contribute to these issues and the calculation of spatial variation in drowning incidence is required. This includes enhancing our understanding and effectiveness of injury prevention interventions from a geospatial and GIS perspective. Given the increase in the availability of spatially referenced drowning data, such as that documented within the UK's Water Incident Database (WAID[7]) and GIS software, it is now timely to consider spatial variation in drowning incidence. Indeed, at the population and community level of intervention, public health and injury prevention often fail to acknowledge the wider structural, environmental or economic determinants of spatial variation in drowning incidents; our study aims to fill this important research gap. We provide evidence on the wider determinants of drowning incidence using a novel, nationwide and recently validated database from the UK across multiple years of data collection (2012-2019[7]).

Accordingly, this study aims to describe the geospatial variation in UK drowning incidents and apply a method that enables priority drowning hotspots to be identified with a view to informing targeted drowning prevention interventions in these areas. Hotspots will be explored in relation to unintentional (i.e., suspected accident[7]) and intentional drownings (i.e., suspected suicide and suspected crime[7]) on the basis that their aetiology may also be different.

2. Methods

2.1 WAID

Since 2009, the Water Incident Database (WAID) has been used to document UK fatal drownings, fatal water-related incidents (collectively recorded as drownings) and non-fatal water-related outcomes. Our previous study verified the data quality of WAID and in doing so we were able to conclude that the database meets the key step of the 2017 WHO drowning prevention implementation guide[11] - to improve data quality describing drowning frequency[7]. For a detailed audit of WAID please refer to Hills et al.[7]. Briefly, data are generated on an incident-by-incident basis by water safety agencies (primary data; e.g., Royal National Lifeboat Institution, His Majesty's Maritime Coastguard Agency, the National Fire Chiefs Council, the Royal Lifesaving Society & the Royal Society for the Prevention of Accidents) following pre-defined fields and taxonomies.

2.2 Data and Study Design

A cross-sectional geospatial study. Specific project approval was granted by the Leeds Trinity University School of Health and Social Sciences research ethics committee (SHSS-2020-03), and a formal data agreement was signed between the authors and RoSPA (the data owner) before any data were exchanged. This written agreement explicitly defined the scope of data use, secure storage, and dissemination of related research findings. This study focused only on data relating to fatal incidents recorded by WAID over a pre-defined period. Accordingly, anonymised WAID data were received for drowning incidents occurring between 1st January 2012 and 31st December 2019, inclusive. After removing any confirmed non-fatal and duplicate cases, the final dataset for this research consisted of 5,051 fatalities by drowning. WAID records each fatal case as a "suspected" outcome as entered to the database by a trained operator. Between 2012 and 2019, 44% (2,244) of cases were suspected as accidental (i.e., unintentional) and 35% (1,746) were suspected as suicidal (i.e., intentional). Accidental drownings were declining and suicidal drownings were increasing. Thereafter the most numerous outcome was "not recorded" (14%; 715); natural causes and crime suspected <4.3% each. Males represented 74% (3,722) of cases primarily in the age group 19 to 35, females represented 20% (1,021) of the sample primarily in the age group 36 to 60 years with the remainder not recorded. Of 5,051 incidents audited, the primary geospatial coordinate of latitude and longitude was identified as missing for 0.0% of cases with the postcode identifier and ordinance survey reference absent in 10.8% and 9.7% of cases, respectively; primarily from cases at sea. Additionally, across 22 potential field entries in WAID the fields of date and time, sex, age, activity and location type (i.e., body of water) were relevant to the onward analysis in the present study.

2.3 Spatial data

Most of the drowning events happen in relation to bodies of open water, we therefore snapped existing data to the nearest water feature or coastline extracted from the OpenStreetMap[28] and combined these data into a spatial network. In the next step, we excluded fatalities without valid coordinates (n = 9), those located in the Republic of Ireland on the basis that they fall outside of the study area (n = 3), those more than 10km from the nearest water feature (n = 85) and domestic events (n=111) as we were only identifying drownings which occurred outside of the home near the water network, giving a total of 4,843 fatalities. Then, as there were records with more than 1 fatality, we identified a number of unique events from the filtered individual cases based on the identical Waidised.ID (and also coordinates and time stamp). Events were filtered to remove events where the cause of death was not recorded, or the fatality was suspected to be due to natural causes. This resulted in 4,117 unique events across the dataset for inclusion in spatial analyses. The recorded WAID drowning outcome was used to group events according to whether any given death was thought to be ''unintentional' (i.e., suspected accidents) or 'intentional' (i.e., suspected homicide or suspected suicide). Crime data were grouped with suicide as the majority of crimes in the dataset were homicides or scenarios where a victim had been entered to the water intentionally by a third party as part of criminal activity[29].

2.4 Geospatial analyses

We used R implementation Density-based spatial clustering of applications with noise (DBSCAN), a well-known data clustering algorithm commonly used in data mining[30], to identify spatial hotspots of drowning events. DBSCAN[31] is a popular density-based clustering method which explores similarity in data based on the minimum density threshold (defined by the minimum number of neighbours, *minPts*) within a radius range (ε or *eps*)[32]. It then forms clusters of data if the individual data points are density-reachable from each other and even the farthest points are density connected[30]. While the method is thoroughly explained elsewhere[30-32] Figure 1 demonstrates concepts of density-reachability and density-connectivity. Both points $Border_1$ and $Border_2$ are density-reachable from a *Core* point, and therefore they are density-connected. Points that are not density reachable from other points in the cluster are classified as *Noise*.

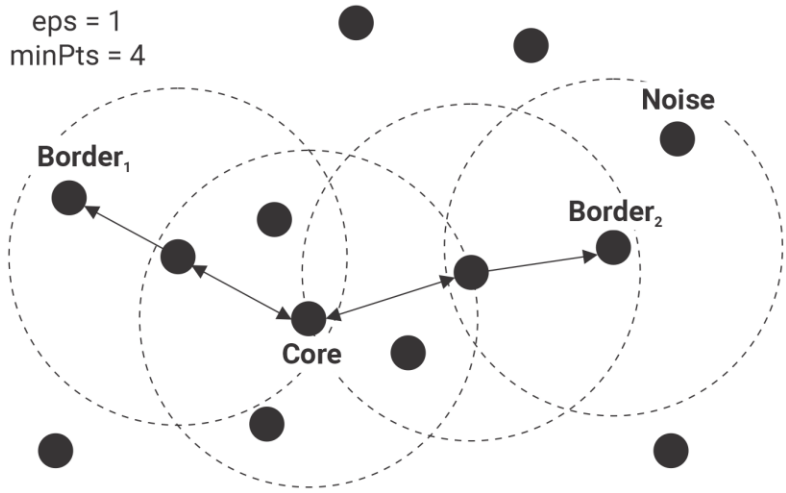

Figure 1. DBSCAN density-reachability and density-connectivity (eps = 1, minPts = 4)

We used three different DBSCAN parameters to identify varying degrees of priority drowning locations based on the clustering of events in those areas. All of them were based on the radius range (*eps*) of 500 m that represents about 5–7 minutes walking distance. Then, for unintentional drownings we combined this with a minimum number (*minPts*) of 4, 6 and 8 unique events (*minPts*) within the range. This equates to around 1 event every other year, 1.5 events every other year and 1 event per year on average (as there are 8 years of data) in 500 m radius to delineate clusters representing *moderate*, *high* and *very high priority* locations. For intentional drownings, we combined this with a minimum number of 4, 8 and 16 unique events (*minPts*) within the range. This equates to around 1 event every other year, 1 event per year and 2 events per year on average. These *minPts* thresholds were determined in consultation with RoSPA and by plotting how the number of identified clusters changed as *eps* and/or *minPts* increased to identify appropriate thresholds based on clear differentiation between the curves. Once the priority group was assigned to the original points, we created a continuous zone by drawing a circular buffer around these points.

3. Results

3.1 Descriptive statistics

In this multinational study (i.e., including all nations of the United Kingdom), there were 2,243 unintentional drowning events and 1,874 intentional events (n = 135 related to suspected crimes and n

= 1,739 suspected suicides) over the eight-year reference period from 2012 to 2019. Table 1 shows the number of events in each category per year. While the number of unintentional drowning events decreases over time, the number of intentional drowning events increased from 2012 to 2013, then decreased and plateaued before increasing again until our final year of analysis (2019).

Table 1: Number of unintentional and intentional drowning events per year (n = 4,117).

Year	Unintentional drowning events	Intentional drowning events (suspected crimes, suspected suicides)
2012	346	234 (48, 186)
2013	350	265 (36, 229)
2014	302	219 (9, 210)
2015	292	205 (12, 193)
2016	256	209 (8, 201)
2017	240	214 (5, 209)
2018	243	241 (9, 232)
2019	214	287 (8, 279)

3.2 Identifying spatial clusters of drowning

This study examined spatial clusters of unintentional (Table 2) and intentional (Table 3) drowning separately. Figure 1 shows a summary of locations of *'very high priority', 'high priority'* and *'moderate priority'* locations. For unintentional drowning events, two areas of *'very high priority'* (*eps = 500m, minPts = 8*) were identified which are visualised in Figure 2 and contained 236 events in two locations (Table 2). These were Brighton beach and Bristol harbour. Moreover, five *'high priority'* locations were identified (*eps = 500m, minPts = 6*), based on seven clusters containing a total of 268 events. These were Beachy Head, York city centre, Stoney Cove, Newquay beach and Glasgow city centre (Figure 3).

While we investigated the spatial clustering of intentional drowning events these are not visualised spatially in this paper due to the sensitive nature of the spatial data and locations involved; these findings have been shared with key stakeholders for onward action. Briefly, we identified four areas of *'very high priority'* (*eps = 500m, minPts = 16*) for intentional drowning events. A further 16 locations were considered *'high priority'* (*eps = 500m, minPts = 8*) based on 18 clusters containing 1,320 events. At the location with the highest incidence of intentional drowning fatalities, 226 events were recorded over the eight-year reference period. This corresponds to a mean rate of ~28 intentional drowning events per year. We have created an interactive map (see Figure 3 for screenshot) to explore the locations of the unintentional drownings, which is available here.

Table 2. Identified spatial clusters and areas of priority for unintentional drowning events (n = 2,243).

Priority zone	Eps (m)	minPts	No. of clusters	Events in clusters	Events outside of clusters	Max no. of events in cluster	Median no. of events in cluster	No. of spatial locations
Very high	500	8	2	236	2007	13	11	2
High	500	6	7	268 (∆32)	1975	13	7	5
Moderate	500	4	27	366 (∆98)	1877	13	5	21

Note: ∆ represents the number of additional events with the change between each subsequent priority location banding.

Table 3. Identified spatial clusters and areas of priority for intentional drowning events (n = 1,874)

Priority zone	Eps (m)	minPts	No. of clusters	Events in clusters	Events outside of clusters	Max no. of events in cluster	Median no. of events in cluster	No. of spatial locations
Very high	500	16	4	386	1488	220	44	4
High	500	8	18	554 (∆168)	1320	226	14	16
Moderate	500	4	54	748 (∆194)	1126	226	7	36

Note: ∆ represents the number of additional events with the change between each subsequent priority location banding.

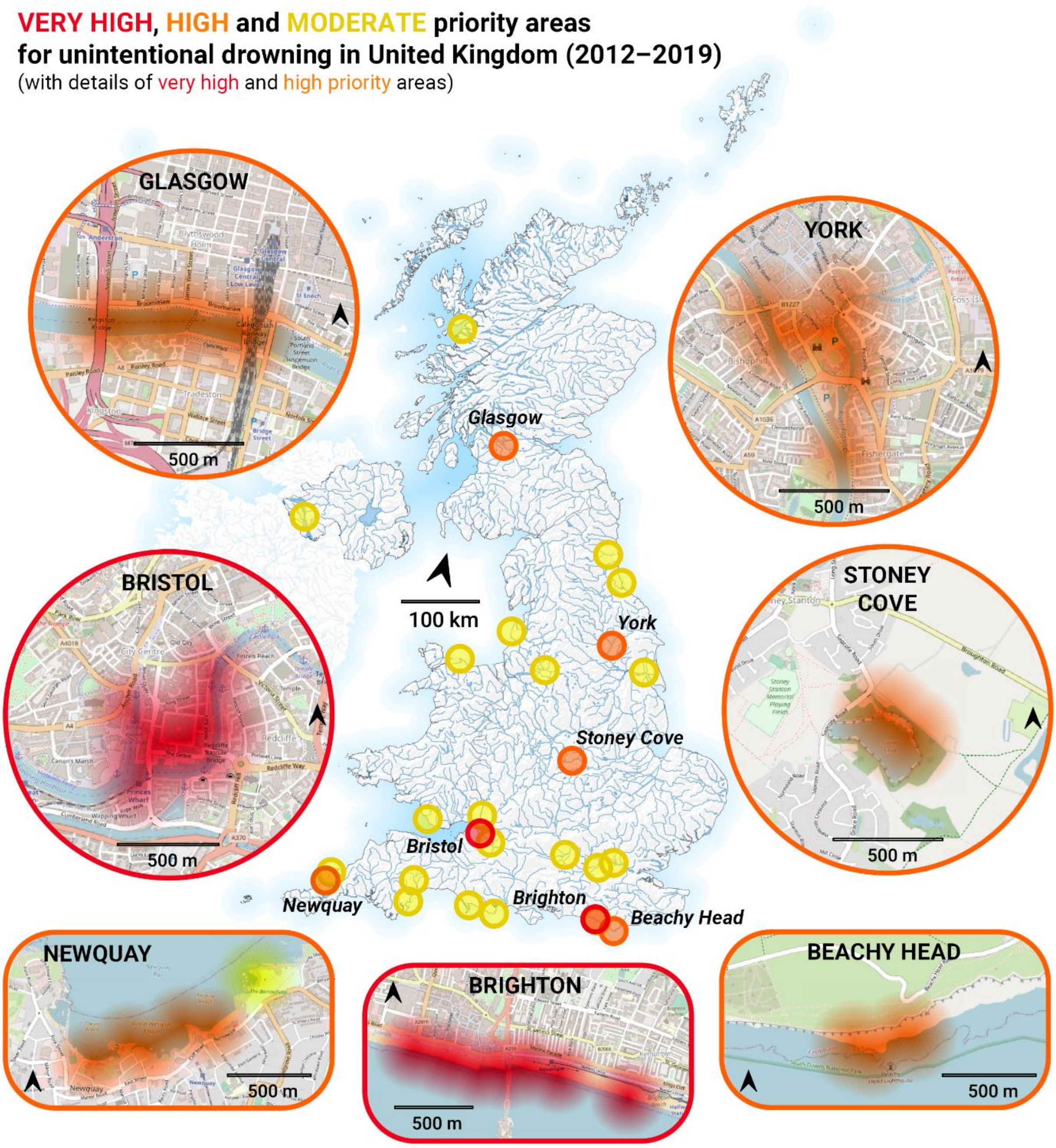

Figure 2. An in depth visualisation of the locations of the two *'very high priority'* areas (red) for unintentional drowning events (*eps* = *500m, minPts* = *8*), the five *'high priority areas'* areas (orange) for unintentional drowning events (*eps* = *500m, minPts* = *6*).

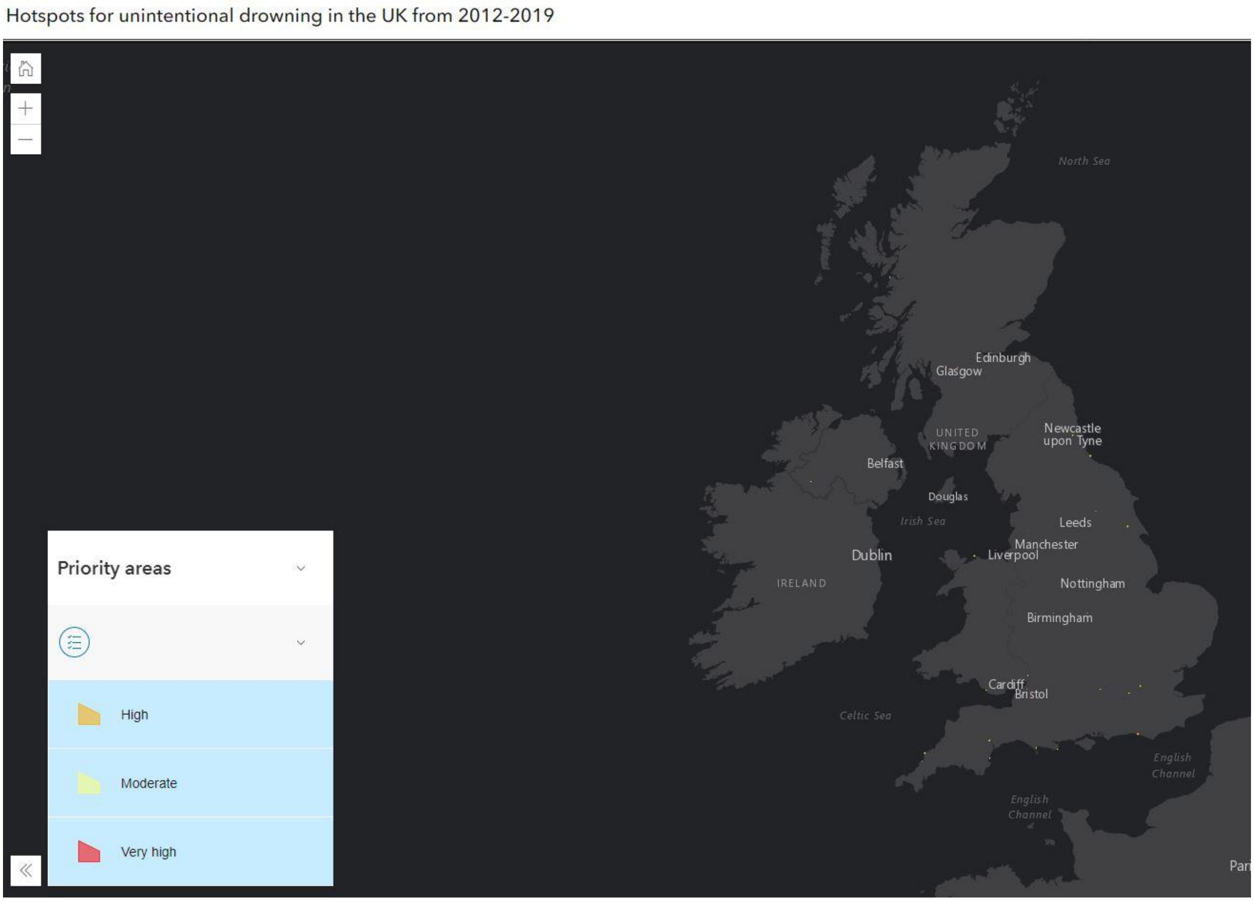

Figure 3. A screenshot of the interactive map developed to display the unintentional drownings.

4. Discussion

This geospatial cross-sectional study aimed to describe spatial variation in unintentional and intentional drowning events across the United Kingdom. We apply a well-known data clustering algorithm commonly used in data mining, in a novel way to identify spatial clusters of drowning events. Importantly, our robust data are drawn from a recently validated nationwide drowning database to achieve this aim[7]. Our clustering algorithm enabled areas (i.e., those containing clusters of drowning events) classified as 'very high priority', 'high priority' and 'moderate priority' to be identified. This study, while intuitive, represents an important step towards informing targeted drowning prevention interventions in these areas.

The number of studies using geospatial clustering methods to investigate unintentional injuries has increased over recent years; however, the literature examining spatial variation in unintentional drownings is scant. For instance, in a review of evidence[21] only two studies used cluster detection methods to investigate the spatial clustering of drowning events. One of the studies demonstrated substantial spatial variation from 2002 to 2008 in drowning density and rate in the state of Georgia, USA[27]. However, little research has been carried out on a nationwide scale and research often relies on reporting rates at an area-level. Our study reports several spatial clusters in one of the first nationwide investigations of its kind.

Our study highlights significant spatial clustering of drowning events. For unintentional drownings, we identified 2 spatial clusters corresponding to 'very high priority' drowning locations. In this study, 'very high priority' for unintentional drownings translates to on average, at least 1 drowning event per year. Moreover, we identified 5 'high priority' locations and 21 'moderate priority' locations. Moderate priority locations had on average, 1 drowning event every other year. Whilst these thresholds for determining these priority locations may seem low these rates reflect 'very high priority', 'high priority' and 'moderate priority' relative to the rest of the study area. Collectively these priority areas represented a combined 16.3% (i.e., 366 events) of the total number of drownings observed in the study period. The majority of these combined drownings took place in very high priority locations (10.52%; 236 events) suggesting where the priority may lie if the resource for intervention is limited. By contrast, these data also highlight the nuanced nature of drownings in the study area and period as 83.7% of unintentional UK drownings do not meet the threshold criteria we set for these priority locations. Hence, there remain some undefined grouping criteria that may distinguish the majority of UK drownings and warrant further investigation. To our knowledge, our findings are some of the first to identify spatial clusters of drowning locations. We are now in a position to inform population- and community-level interventions for public health and injury prevention which have to date often failed to acknowledge the wider structural, environmental or economic determinants of spatial variation in occurrence of drowning incidence.

While prevention campaigns often focus on unintentional drowning, a high proportion of drowning events are intentional (i.e., 35% across the present study's analysis period[7]). There is substantial variation in prevalence by country. For instance, a study from South Korea showed that approximately three-quarters of drowning cases admitted to emergency departments between 1998 and 2011 had drowned themselves intentionally[33]. However, a more recent Australian study demonstrated that intentional drowning deaths in Australia represented around 17% of all drowning deaths between 2006 and 2014[34]. Over a similar and more recent study epoch, albeit in different overall national populations (i.e., population greater in the UK), we saw double the proportion of suicidal drownings in the UK (i.e., 35%) than Australia[34] highlighting perhaps an urgent need for intervention[7]. Nevertheless, intentional drowning is a little studied issue worldwide and even less research has considered how geospatial methods can be used to identify geographic areas associated with intentional drowning events and to target prevention efforts. To the author's knowledge, our study is the first internationally to identify distinct spatial clusters of intentional drowning locations. While the data are not shown visually due to the sensitive nature of the location-based data, we identified 4 'very high priority', 16 'high priority' and 36 'moderate priority' areas for intentional drowning across the UK (Table 3). There was a far greater number (i.e., 748 events) and proportion of the 1,874 intentional drowning events (i.e., 39.9%) that met the 'moderate priority' location threshold for intentional drownings compared to unintentional drownings (i.e., 16.3%). These data indicate detailed study and drowning prevention intervention across these 36 locations has the potential to substantially reduce the number of intentional drownings nationwide. Nevertheless, it is still prudent to establish any grouping characteristics for the remaining 60.1% of intentional drowning events to drive effective intervention in these cases. There is also greater spread in the number of events between our priority classifications for intentional drownings (i.e., 39.9%, 29.6%, 20.6%) compared to unintentional (16.3%, 11.9%, 10.5%) across moderate to very high priority areas; albeit across different minimum points (*minPts*) thresholds for the high (8 *vs* 6) and very high priority locations (16 *vs* 8). Collectively our findings highlight key differences in patterns of intentional drownings and a potential gap between the traditional focus of drowning prevention aimed at preventing unintentional drowning and a lack of focus on the prevention of intentional drowning[35]. A renewed focus on collaborations between drowning prevention organisations, public health and mental health institutions to achieve a coordinated effort to prevent intentional death by drowning could help.

The promotion of research, and the development of innovative drowning prevention tools and technology, as showcased in the present study, addresses one of the United Nations (UN) priority elements endorsed as part of the UN resolution on global drowning prevention launched in 2021[2]. To our knowledge, no study has utilised the DBSCAN technique to identify spatial clusters of drownings for both unintentional and intentional drowning events. We intend to annually update the data entered to the algorithm and make the results publicly available as a trend analysis tool to detect new patterns in UK drownings and to inform prevention activities in locations where clusters develop. Indeed, it is a limitation that our analysis does not include the two years of most recent data from 2020 and 2021. Yet the patterns of drownings in these years are probably influenced by the COVID-19 pandemic in a similar way to other public health outcomes[36]; future studies will check this premise. As such the 2012 to 2019 WAID data that could be considered "normal" from a societal perspective.

The findings presented in the present study contribute to the WHO's drowning prevention implementation guide step to identify risk factors[11]. They also inform progress, at approximately the halfway point, of the UK drowning prevention strategy which aims to halve unintentional drownings by 2026[37]. For unintentional drownings, the very high priority and high priority locations may carry a geographical risk to the population who reside at or visit these areas. These bodies of water reflect the predominance of drowning in-land in rivers, a harbour and a quarry compared to three locations that could be defined as coastal (i.e., beach feature). Of the very high priority for intentional drownings (not visualised) two are inland (rivers), one is coastal and one is on a tidal estuary. It is now prudent to establish the additional characteristics such as population, exposure, or demographics that distinguish these locations as being high priority over other similar bodies of water that are characteristically the same but do not record the same number of types of drownings. Particularly in the case of estimating the exposure of the population to a risk area, it is likely that a city centre location experiences a greater number of visitors exposed to the hazard and hence a more remote location that records a similar or greater number of drownings with fewer visitations is a more potent risk. It is also prudent to give feedback to local and national stakeholders in these areas to inform the prevention efforts in these locations.

Whilst our study is able to say *where* drownings are occurring and *how* often leading to important insights on the risk associated with particular areas, we are unable to say *why* drownings may be occurring [38]. While this was far beyond the scope of our paper, it is important to acknowledge future work could investigate in more depth the types of environmental characteristics, often associated with drowning events, both intentional and unintentional. For instance, in person or digital environmental scans could observe common characteristics across the clustered drowning areas. Previous research has used such audits to examine the quality [39] or aesthetic features of the environment[40-42]. Plausible targets include characteristics of the natural and built environment such as cold water[43], rip currents[44] and proximity of alcohol outlets[45] which should be investigated in future research for their influence on drowning likelihood. Moreover, future research could explore in more depth using secondary data other reasons as to why high-priority locations may occur. For instance, in the field of criminal geography a plethora of evidence has investigated why hot spots of crime may occur or how the access and availability of alcohol outlets are related to adverse social outcomes such as crime or hazardous drinking[46-51]. It is therefore plausible that in this new application of geospatial methods similar approaches could be taken to explore why or what key factors may lead to an increase in drowning incidence within a particular hot spot. Such evidence applied in this drowning context may therefore elucidate not only *when* and *how often* but also *why* drowning may be occurring in these areas enabling even more specific evidence for policy to act.

It is also important to reaffirm here that using geospatial data science to inform drowning prevention this represents somewhat a paradigm shift. First, many interventions and strategies have historically focused on the individual-level or environmental modification at a micro-environment or local scale including but not limited to, lifeguard presence[42], promoting adult supervision for children[9, 34, 52], water familiarisation interventions[53], placement of rescue equipment and improving early basic life support[54]. Interestingly, a recent 2023 review of interventions for drowning prevention among adults[10] found that there had been a shift away since a previous review[15] (in 2016) from a predominance of behavioural-only strategies which emphasise education towards population-level interventions[10]. This is important, as regulatory or environmental changes are more likely to produce population-level outcomes, which are cost-effective long term as well as translate into sustained behaviour change [16, 17, 55]. Indeed, in the recent review all six population-level interventions demonstrated a considerable reduction in the number of drownings in the population sustained over time[10]. This is not to say that individual or behavioural interventions are not important or successful. However, it is a worthy reminder that the causes of both intentional and unintentional drowning are multifaceted in aetiology. For instance, recent evidence from New Zealand and Australia has shown that despite a decade-long educational campaign in New Zealand only 40% of rock-fishers self-reported always/often wearing a lifejacket[56] and in Victoria, Australia, a three-year educational campaign with rock fishers produced no change in lifejacket use [57]. Therefore, multi-strategy prevention efforts targeting both the person at risk and structural considerations such as using regulatory options are more likely to be successful than programs relying on a single strategy[10, 17].

This study is not without limitation. We used the DBSCAN algorithm to identify spatial clusters of drowning locations. This density-based method is sensitive to the selection of the radius range (*eps*) and a minimum number of neighbouring points (*minPts*) within the range. There are existing rules of thumb on how to select these such as using a plot k-Nearest Neighbour Distances to identify *eps*[30] or (at least) double the dimension of data for the selection of *minPts.* While we ran sensitivity analyses (*eps* in *[0; 10,000]* by 250m, minPts *[2;100]*) to understand the clusters creation, we chose to select the parameters (with stakeholder guidance) based on the knowledge of geographical domain and data. We also analysed data only in the two-dimensional spatial domain while there is also information about the date (and year) available that would allow for additional usage of methods such as ST-DBSCAN[58] that evaluates the points density in spatial and temporal domain. This limitation is not easily overcome as existing literature often relies on calculating a rate of drowning incidence per population thereby requiring an accurate population denominator such as from a census estimate. Moreover, this approach can be spurious as we know that not all drowning events occur in the same area in which an individual resides which additionally require an estimation of population exposure[59]. Finally, our study does not enable the distinction between “outcomes” at these locations which were decided against pre-defined criteria by a trained operator independent of the study team. Future research should further investigate in more depth the characteristics of these very high priority, high priority and moderate priority areas to provide more specific guidance for policy and drowning prevention efforts.

5. Conclusion

In this large multiyear, nationwide and validated dataset of drownings within the Water Incident Database (WAID) we identified spatial clusters of both unintentional and intentional drowning events defined by severity as ‘very high priority’, ‘high priority’ and ‘moderate priority’. Identifying, spatial variation in drowning incidence and priority locations forms the first significant part of a better understanding of the wider determinants of drowning risk and may be an important consideration for the implementation of water safety interventions.

6. References

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