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Forecasting bathing water quality in the UK: A critical review

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Abstract

Climate change is altering rainfall patterns resulting in increasing variability and intensity of rainfall events worldwide. Increases to short duration, intense rainfall (i.e., convective rainfall), will lead to increases in sewage overflow and run-off from agricultural land. Such events generate spikes in micro-organisms from feces and manure, especially *Escherichia coli* and intestinal enterococci, that temporarily end up in bathing waters posing serious health risks to bathers. Forecasting of bathing water quality associated with convective rainfall presents a distinctive forecasting challenge due to high uncertainties associated with predicting the timing, location, and impact of such events. In this article, we review examples of bathing water quality forecasting practices, with a focus on the United Kingdom where convective rainfall in the summer bathing water season is a particular concern, and question whether the current approach is robust in a changing climate. We discuss potential upgrades in bathing water forecasting and identify the main challenges that must be addressed before an improved framework for bathing water forecasting can be achieved. Although developments in meteorological and hydrological short-range forecasting capabilities are promising, convective rainfall forecasting has significant predictability limits. We suggest taking full advantage of short-range forecasts to provide sub-daily bathing water forecasts, focusing on targeted bathing water monitoring regimes to improve model accuracy with the ultimate goal of providing improved information and guidance for beach users.

This article is categorized under:

Science of Water > Water and Environmental Change

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Human Water > Water Governance
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bathing waters, climate change, forecasting, operational, water quality

1 | INTRODUCTION

Bathing water quality (BWQ) and protection is a matter of concern for public health, because contact with fecal bacterium-contaminated coastal waters, especially with *Escherichia coli* (EC) and intestinal enterococci (IE) may result in illness (Byappanahalli et al., 2012; Haile et al., 1999; Korajkic et al., 2018; Kristich et al., 2014; O'Mullan et al., 2017; Swinscoe et al., 2018; Viau et al., 2011). An 8-year-old girl died, and another child was admitted to hospital following an outbreak of EC at the holiday resort of Dawlish Warren, south Devon, in August 1999 (The Guardian, 1999). In 2004, holidaymakers were diagnosed with EC poisoning after bathing at Watergate Bay, Cornwall (BBC, 2004). In both cases contact with contaminated sea and stream waters were the main suspects. Between October 1, 2021 and September 30, 2022, 720 water users reported getting ill after entering bathing waters across England, double the number reported in 2020/2021 (SAS, 2022).

Coastal and freshwater habitats generally do not support fecal bacteria growth such as EC and IE. Their presence is evidence of point and/or diffuse source pollution, or resuspension from environmental reservoirs (Pandey et al., 2014). In the United Kingdom and other developed countries, most of the time such pollution stays at source, only reaching bathing water following mobilization after heavy rainfall, especially short-duration rainfall, which causes drainage systems to be more susceptible due to increased peak flow volumes and shorter times to peak flow (Agudelo Higuita & Huycke, 2014; Al Aukidy & Verlicchi, 2017; Allan et al., 2020; Bedri et al., 2016; Campos et al., 2013; Cho et al., 2010; Heasley et al., 2021; Herrig et al., 2019; Kay & Fawell, 2007; Tornevi et al., 2014; Wyer et al., 2018).

Real-time monitoring and analysis of the microbiological status of bathing water quality is impractical due to the time that elapses between sample collection and laboratory analysis (Motamarri & Boccelli, 2012; Oliver, Porter, et al., 2016; Tornevi et al., 2014; USEPA, 2010). During this time, the public may be exposed to elevated levels of pathogenic bacteria (bacteria that can cause disease) increasing the risk of FIO-driven gastrointestinal, respiratory, and skin infections (Fleisher et al., 2010; Korajkic et al., 2018). Remote sensing methods including imaging spectrometry have been used as an alternative to help obtain up-to-date and cost-effective information for bathing waters protection (Cherif et al., 2019; Giardino et al., 2019; Grimes et al., 2014); however, these techniques must evolve further to be considered for operational use (Tyler et al., 2016). Forecasting of bathing water quality is therefore vital to inform the public of the potential health risks and allow them to make informed choices (Commission and Bruyninckx, 2021).

Bathing water quality forecasts are based on the modeled relationship between FIO and multiple environmental variables. For example, the presence of FIO is known to increase with an increase in rainfall intensity and duration and decrease with an increase in received and extra-terrestrial UV irradiance. Although variables are site specific the relationships are mainly driven by rainfall (Fulke et al., 2019; Grant et al., 2001; Kay et al., 2005, 2018; Rochelle-Newall et al., 2015; Thoe et al., 2014). Forecasting of bathing waters involves two steps. First, statistical modeling using past/historic data, commonly multiple linear regression (MLR), is used to identify sets of environmental predictor variables that best explain the distribution of IE at a specific bathing water, together with the relative contribution of each variable to the total explained variance (Searcy et al., 2018). Next, live forecasting combines the established statistical model with available real time hydrometeorological data (e.g., rainfall radar data, wind speed, tide height) (Chan et al., 2012; Stidson et al., 2012; Thoe et al., 2014; Tyrrell, 2017) to provide a warning when a set IE threshold is forecast to be exceeded (Kay et al., 2012; Wyer et al., 2018). Less sophisticated models are based on rainfall and flow thresholds only, which are site, gauge, and time specific (Stidson et al., 2012).

Anthropogenic climate change is causing global temperature to rise (Guzman, 2014). As described by the Clausius–Clapeyron (CC) equation, warmer air can generally hold 7% more water for every 1°C temperature increase (Ambaum, 2010). Relatively continuous and uniformly intense stratiform precipitation increases with temperature at the CC rate. Convective precipitation associated with high-intensity downpours exceeds the CC rate (Cotterill et al., 2021; Fowler et al., 2021). This suggests that convective precipitation is more sensitive to temperature increases than stratiform precipitation, but the relative contributions of these two types of precipitation have been challenging to establish (Berg et al., 2013). This also implies that extreme intense rainfall events may intensify more quickly and sooner than projected, resulting in increased severity of bathing waters pollution impacts, especially in the summer months, which form the core of the bathing season (Bocheva et al., 2009; Hawkins et al., 2020; Kahraman et al., 2021; Kendon et al., 2014, 2018, 2023; Kharin et al., 2013; Met Office, 2019; Osborn et al., 2000; Xu et al., 2018). Convective storms are not only expected to have higher peak intensity, but also longer duration and become more frequent across the whole of Europe (Kahraman et al., 2021).

Worldwide, water infrastructure has already been struggling to keep pace with changes to rainfall and a growing population (Rouse, 2014; Suchowska-Kisielewicz & Nowogoński, 2021). The global water monitoring program reported one-third of all rivers in Africa, Asia, and Latin America severely affected by pathogen pollution (UNEP, 2016). In the United Kingdom, the post-Brexit agenda, which now focuses on a nation resilient to climate change, has created an opportunity for funding to mitigate the worsening impacts of the climate emergency (Gill et al., 2021). Improvements in forecasting of bathing water quality would help minimize some of those impacts.

In this review, we discuss shortcomings in current UK operational practice in understanding, monitoring, and forecasting of bathing water quality (focusing on England) and address the challenges ahead. First, we discuss the need to improve forecasting of bathing waters in a changing climate and current scientific understanding of factors influencing bathing water quality and its complexity. Next, we explain why and how bathing water quality is measured and forecasted. We review the current methods for bathing water forecasting and highlight some weaknesses. We question: does operational practice reflect current understanding of the science and take advantage of the best available weather forecasts? Finally, we discuss challenges that need to be addressed before an improved framework for bathing water forecasting in England can be realized.

2 | THE NEED TO IMPROVE FORECASTING OF BATHING WATER QUALITY IN A CHANGING CLIMATE

Rainfall has a strong influence on bathing water quality as it triggers sewage overflow and agricultural runoff that contains bacteria potentially harmful to people (Crowther et al., 2001; Economy et al., 2019; Fleisher et al., 2010). So how does climate change affect rainfall? Warmer air can hold more water and therefore has the potential to increase rainfall intensity and the associated risk of poor bathing water quality. Scientists agree that climate change is altering rainfall patterns resulting in increasing variability and intensity of rainfall events globally (Blenkinsop et al., 2017; Kitoh & Endo, 2016; Kyselý & Beranová, 2009; O'Gorman, 2015).

However, regional weather patterns are also likely to change (Darwish et al., 2021; Shepherd, 2014). Climate change projections over the United Kingdom show an increased chance of wetter winters (Davies, 2021; Kendon et al., 2023). UK's summers are likely to be drier overall, but an increase in the frequency and intensity of short duration rainfall convective rainfall (such as that from thunderstorms) is projected (Jones et al., 2014; Kendon et al., 2014, 2018, 2023; Kent et al., 2022).

Data show that short-duration intense precipitation is more sensitive to temperature increases than stratiform precipitation, that is, generally characterized by continuous and uniform downpours (Barbero et al., 2017; Berg et al., 2013; Fowler et al., 2021; Xiao et al., 2016). It is projected that the number of convective sub-daily summer rainfall events will increase in the United Kingdom due to climate change (Bürger et al., 2019; Kendon et al., 2023). Pollution of bathing waters can be caused by stratiform or convective rainfall, however, it is the latter that poses a particular challenge to forecast accurately, therefore, an increase in the number of convective rainfall events during the summer bathing water season increases the likelihood of incorrectly forecasted bathing water failures.

3 | BIOLOGICAL, CHEMICAL, AND PHYSICAL FACTORS INFLUENCING BATHING WATER QUALITY

Forecasting of bathing waters is challenging due to the complexity of biological, chemical, and physical factors affecting bacteria concentrations in bathing waters as illustrated in Figure 1. Although, all the processes included in Figure 1 are well understood in controlled laboratory environments, there is a lack of research in the real environment, which limits understanding of interactions at catchment scale. Microbiological pollution sources to bathing waters can be divided into two categories: natural and artificial.

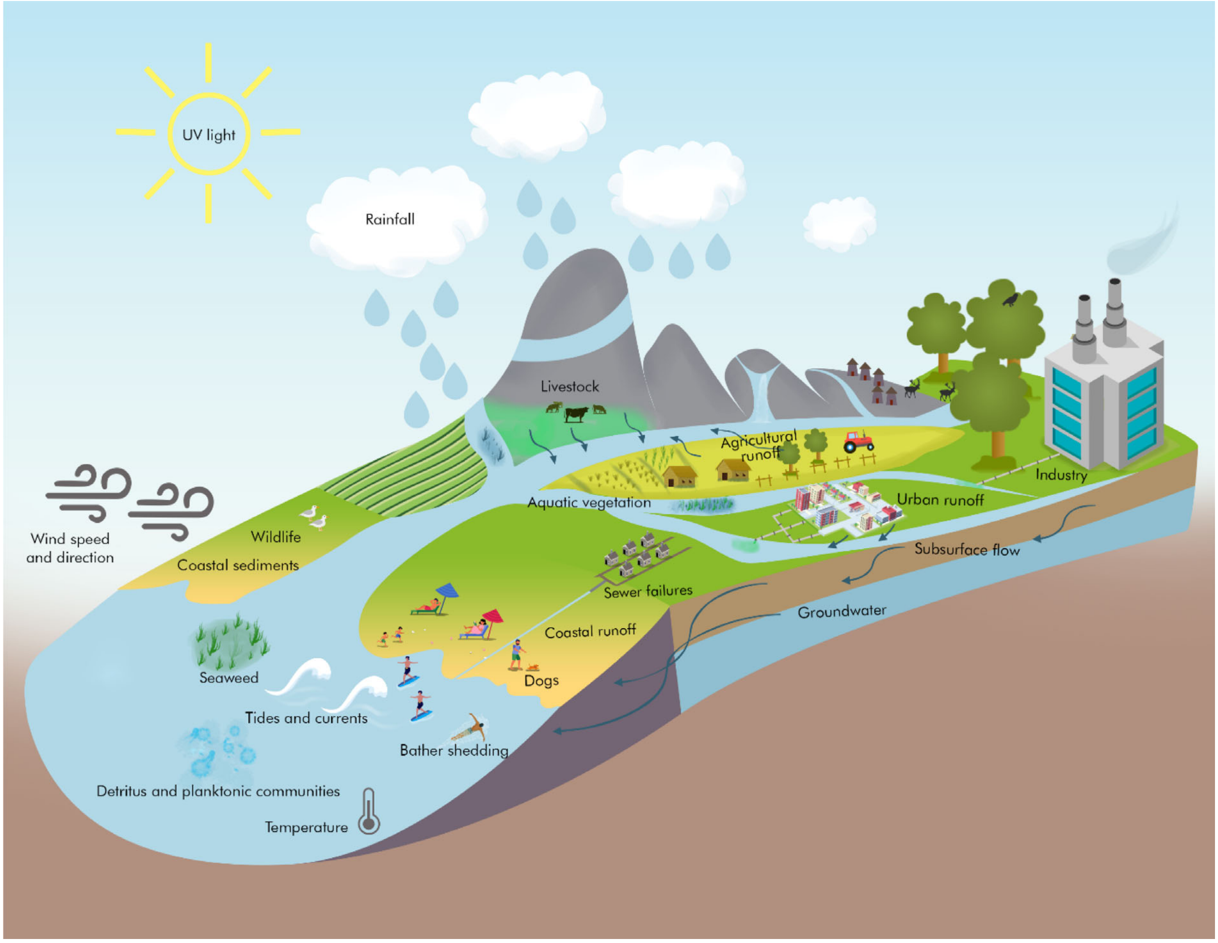

FIGURE 1 Factors influencing bathing water quality.

High bacteria levels have been recorded in natural sources including marine, intertidal, and freshwater sediments, vegetation, groundwaters, tidal saltwater marshes, and beach aquifers (Anderson et al., 2005; Boehm et al., 2004; Ferguson et al., 2005; Obiri-Danso & Jones, 2000). Furthermore, high Enterococci densities have been observed in seaweed (Swinscoe et al., 2018), detritus, planktonic communities (Mote et al., 2012), and other aquatic vegetation (Badgley et al., 2010; Whitman et al., 2003). Enterococci concentrations may also be driven by their presence in groundwater inputs (saline and fresh) from the beach aquifer (Boehm et al., 2004). Wild bird and dog feces near the high-water line might also considerably increase total count of bacteria in bathing waters (Kutkowska et al., 2019; Layton et al., 2009). Additional pollution sources during the summer season such as bather shedding (shedding microorganisms from their own bodies) due to increased numbers of bathers may also play a part, especially at overcrowded beaches (Li et al., 2021).

Artificial sources of bacteria including commercial and domestic sewage are major contributors to pollution of coastal waters worldwide (Brandão et al., 2020). Combined sewer overflows (CSOs) provide an outlet for flows that exceed the hydraulic capacity of combined sewerage systems, on which much of the UK's sewer infrastructure relies (Al Aukidy & Verlicchi, 2017; Botturi et al., 2021). During heavy rainfall events a mixture of stormwater and raw sewage is directly discharged into receiving watercourses causing deterioration of water quality (Poopipattana et al., 2021). Additionally, water companies dump untreated or partially treated sewage in rivers on a regular basis, often breaching the terms of permits that allow such practices only in exceptional circumstances, including storm overflows at wastewater treatment works due to heavy rainfall, emergency overflows due to equipment failure, and CSOs elsewhere on the network (Gardiner et al., 2022). Stormwater, which includes rainwater collected from roofs and roads, has been also recognized as a source of fecal indicators and pathogens to the bathing waters (Ahmed et al., 2020). Poorly located and maintained septic tanks, can also pollute surface and groundwater systems (Smith et al., 2020). Agricultural and rural land management practices also have a significant impact on the levels of FIOs in bathing waters. Farms are a point source of contamination generating large volumes of manures, contaminated water, and associated run-off during rainfall events (Dufour, 2013). Livestock crossing watercourses and excretion while drinking can be a significant source of FIO to the river systems as well as fecal pollution from non-point sources such as pastoral agricultural land (Aitken, 2003; Kay et al., 2005, 2018). Inappropriate agricultural practice such as slurry release during dry weather conditions and knowingly polluting watercourses with farm animal waste are also common in the United Kingdom (House of Commons Enviromental Audit Committee, 2022).

The sources need a trigger to be transported to bathing waters. Bathing water failures are associated with both short-duration intense (1–3 h) and long-duration (>1 day) rainfall (Tyrrell, 2017). However, short-duration intense rainfall events in the summer are of particular interest here because it is these events which occur during the bathing water season, the high sudden volumes of rainfall can easily overwhelm drainage systems leading to a high risk of sewage overflows, while the high rates of overland flow generated from these rainstorms can pick up agricultural pollutants and transport them to the river (Gill et al., 2021). Thus, once the sources are triggered, fecal contamination presents a risk of disease transmission via exposure pathways, with the most common being rivers, streams, drains, and direct rainfall runoff (Aitken, 2003; Hatvani et al., 2018). The impact of a freshwater stream on a coastal bathing water will be dependent on its discharge and bacteria levels as well as its proximity to the bathing water. The overall input or "loading" of bacteria (recorded concentration of bacteria multiplied by streamflow) is important, high flows with low bacteria levels can have as much impact as low flows with high bacteria levels. As the stream enters the bathing water many factors such as stream base flow conditions, currents, turbidity, suspended solids, conductivity, dissolved oxygen, pH, and solar irradiation all influence bacterial persistence and die-off rates, and the final bacteria levels in the water column (Bouchalová et al., 2013; Cho et al., 2010; Francy et al., 2013; Vermeulen & Hofstra, 2014).

Transport of FIO in coastal waters is driven via tides and currents, allowing their movement from a source, such as rivers and streams, to a distant bathing water or away from it (Kim et al., 2004) and currents also influence bacterial population decay by cell separation (de Brauwere et al., 2014). Flooding tides tend to dilute nearshore FIO sources which results in a reduction in bacterial concentration (Boehm & Weisberg, 2005; Coelho et al., 1999; Mohandass et al., 2010). Falling ebb tides may allow drainage of IE generated in tidal saltwater marshes and beach aquifers (Boehm et al., 2004) causing an increase in concentrations of FIO in bathing waters (Boehm et al., 2004; Grant et al., 2001). Spring tides may influence the hydrologic cycling of FIOs sources at the water line and upper reaches of the tidal zone, especially if the spring tides are higher than average (Grant et al., 2001). For example, samples collected from 60 marine beaches in Southern California, were twice as likely not to meet compliance standards during spring tides as compared with neap tides, while spring-ebb tides were found to yield the highest IE concentrations and the greatest chance of exceeding the compliance standard (Boehm & Weisberg, 2005). The movement of bacteria through the receiving water, and the resulting bathing water quality, is also controlled by the direction and magnitude of wind and waves (EPA, 2016). FIO concentrations tend to increase with rising wind speed and direction (Dueker et al., 2017; Hatvani et al., 2018; Lewis et al., 2013; Smith et al., 1999). With respect to wind direction, studies show that the numbers of bacteria present in a sample were considerably higher when the sample site lay downwind of the outfall (Dueker et al., 2017; Smith et al., 1999). Increasing wind speed increases shoreline turbulence resulting in resuspension of bacteria from the sediments and soils (Hatvani et al., 2018), however, wind speed only has a significant role in bathing waters located downstream of a sewage outfall or freshwater input (Smith et al., 1999).

Sunlight and salinity are the two major factors governing the environmental persistence of IE in bathing waters (Chudoba et al., 2013; Gordon et al., 2002). Biological decay of bacteria can be modulated and minimized by solar radiation (Kay et al., 2005; Sinton et al., 1999, 2002) via processes such as hindrance of bacterial production (Aas et al., 1996), bacterial biomass (Helbling et al., 1995), and inhibition of metabolically important enzymes (Müller-Niklas et al., 1995). Sunlight may cause damage to the cells via direct solar radiation damage to nucleic acids and other cellular components (Schuch & Menck, 2010), and/or the enhanced photodegradation driven by reactive oxygen species from organic matter (Appiani & McNeill, 2015). Sunlight wavelengths reaching bathing waters depend on latitude, the diurnal cycle of solar elevation, and cloud cover, while transmission of solar radiation in the water column is further determined by turbidity produced by suspended material (Kay et al., 2005; Sinton et al., 1994, 1999). The Genus *Enterococcus* has a unique ability to grow in the presence of salt (as high as 6.5% NaCl). The greater salt tolerance of IE than of EC and other fecal coliforms contributes to their better performance as indicators of human health risk in marine recreational waters (Boehm & Sassoubre, 2014). However, higher salinities increase rates of inactivation of IE and other bacteria (Carr et al., 2010; Davies et al., 1995; Dorsey et al., 2010; Kay et al., 2005; Menon et al., 2003; Sinton et al., 2002; Viau et al., 2011).

4 | WHY AND HOW DO WE MEASURE BATHING WATER QUALITY?

Worldwide bathing water quality is measured for legal reasons and to provide guidance allowing beach users to make informed decisions about associated risks with waters contaminated by fecal matter (WHO, 2003). Pathogenic and non-pathogenic IE and EC strains exist, however, only pathogenic strains cause intestinal disease in humans. Direct monitoring of waterborne pathogenic strains only would be costly, technically challenging, and in some cases not feasible. Therefore, bathing waters are monitored for the presence of FIO that includes both pathogenic and non-pathogenic forms bacteria strains (Korajkic et al., 2018). The type of FIO measured and values used in bathing water guidelines vary by country, with the most commonly used FIO including IE, EC, total fecal coliforms, *Clostridium perfringens*, and Bacteriophages (WHO, 2003), as these bacteria are commonly found and distributed in the feces of humans and animals (Anderson et al., 2005; Boehm et al., 2002; Cabral, 2010; Kay et al., 2005). The greater salt tolerance of IE than other fecal coliforms makes it the most frequently used monitoring proxy for pathogens in coastal bathing waters worldwide (Davies et al., 1995; Dorsey et al., 2010; Kay et al., 2005; Sinclair et al., 2012). Additionally, a strong dose–response relationship between IE in marine environments and health outcomes makes it the most used indicator for forecasting applications (Byappanahalli et al., 2012; Davies et al., 1995; Dorsey et al., 2010; Kay et al., 2005).

In Europe and the UK water quality classification can be divided into long and short-term classification. The long-term classification is required by the EU Bathing Water Directive (BWD), first introduced in 1976 and further revised in 2006 (rBWD) (2006/7/EC) (Commission and Bruyninckx, 2021; Tyrrell, 2017). After Brexit (January 31, 2020) the United Kingdom uses rBWD to represent all of this legislation going forward and laws have been transposed in the Bathing Water Regulation legislation (full). Short-term classification remains advisory only by the rBWD. The United Kingdom is preparing to update environmental regulations by setting higher standards, greater punishments, more powers for regulators, and a greater burden on industries to shoulder the costs of regulation (Ofwat, 2023).

4.1 | Long-term bathing water quality

Long-term bathing water quality monitoring, based on rBWD (2006/7/EC, 2006), is carried out to confirm which designated bathing waters pose risk to bathers, and allow appropriate remediation measures to take place. Monitoring of water quality runs during the bathing season (e.g., in England from May 1 to September 25) and requires up to 20 samples to be taken from each designated bathing water throughout this time (2006/7/EC, 2006). The United Kingdom has over 600 designated bathing water locations, pred. These are sites that are popular for swimming and paddling and have been designated under the Bathing Water Regulations. Most of these are coastal, at the start of 2023 there were only three inland bathing waters registered in England, but the number is slowly increasing (https://environment.data.gov.uk/bwq/profiles/). Operationally this approach may be practical, however, it does not reflect the dynamics of IE fate in a particular bathing water and its related catchment (Figure 1). This strategy will also become problematic as popularity of cold-water swimming is growing (Gay et al., 2022) as well as climate change and associated temperature rises encourage people to swim outside the current bathing water season.

At the end of each bathing water season, each designated bathing water location is classified. There are four levels of classification under the rBWD, derived from the IE and EC concentrations recorded over a 4-year period. The class is determined by the worst parameter and based on the 95th percentile, informing that pollution occurs for <5% of the time (Table 1). Revised BWD advises the use of EC as well as IE to classify bathing water quality based on a No

TABLE 1 Long term coastal Bathing waters classification rBWD (2006/7/EC).

Classification	Coastal and transitional waters
Excellent—The highest, cleanest class (95% of samples must meet the limits to gain this classification)	Intestinal enterococci—100 cfu/100 mL *E. coli*—250 cfu/100 mL
Good—Generally good quality (95% of samples must meet the limits to gain this classification)	Intestinal enterococci—200 cfu/100 mL *E. coli*—500 cfu/100 mL
Sufficient—The minimum acceptable standard for bathing (90% of samples must meet the limits to gain this classification)	Intestinal enterococci—185 cfu/100 mL *E. coli*—500 cfu/100 mL
Poor—Swimming and paddling is not advised as the water quality has not met the minimum standard	Waters that do not meet the higher classifications

Observed Adverse Effect Level (NOAEL) (Wiedenmann et al., 2006) still IE has been favored as an indicator of pollution for forecasting purposes. This is because the Genus *Enterococcus* has a unique ability to grow in the presence of salt. The greater salt tolerance of IE than of EC and other fecal coliforms contributes to their better performance as indicators of human health risk in marine recreational waters (Boehm & Sassoubre, 2014). Considering the management of bathing waters, the long-term classification will not reflect the true state of the environment nor the daily microbiological status of the bathing water quality. Water quality exceedances are very dynamic and short-lived events, the chance of capturing the elevated levels of IE using just planned compliance sampling is exceptionally low (5%) (Leecaster & Weisberg, 2001).

In Europe, long-term classification for designated bathing waters can be found on regulator websites and beach signs. The classification is illustrated as standardized pictorial symbols to reflect "Excellent," "Good," "Sufficient," and "Poor" bathing water quality classification, which was fully implemented in 2015 rBWD (Figure 2). If water is classified as Poor, then the symbol for "Poor" together with a sign showing advice against bathing must be displayed in the following year. A sign displaying a "Poor" classification and advice against bathing does not mean bathing is banned or that a beach is closed. There are interpretation issues with rBWD bathing water quality signage (Papadopoulou et al., 2018), for example, the symbols of classifications provide little information in terms of what the classification means for health risk. This means that few beach users would understand how this relates to them becoming ill from exposure to bathing water at a particular beach (Oliver, Hanley, et al., 2016). Regulators provide little information on how classification reflects associated likelihood of illness (Pratap et al., 2013).

4.2 | Short-term bathing water quality

Microbiological analyses for indicators of pathogen are not fit for assessing the true state of the microbiological environment due to a significant time lag between sample collection and analysis (Rodrigues & Cunha, 2017). Such limited representation in time and space is a significant problem in enumeration of IE and other FIOs used to assess bathing water quality. For this reason, short-term water quality is forecasted to provide information to the public and achieve compliance with the bathing water regulations. The implementation of early warning systems for bathing waters, which are subject to short-term pollution events, was advised by the rBWD. Existing coastal water quality prediction tools provide short-term forecasts of bathing water quality based on the modeled relationship between IE and multiple environmental variables and real-time hydrometeorological data from observations and forecasts (Gutiérrez et al., 2010; Stidson et al., 2012; Thoe et al., 2014, 2015; Tyrrell, 2017). Short-term pollution forecasts are translated into a simple advisory message displayed for a particular day and beach (Oliver, Hanley, et al., 2016). The messages communicating advice against bathing are displayed up to 9.00 a.m. GMT in Europe, at the designated beach signs, and stay-unchanged for the day (Chan et al., 2012; Stidson et al., 2012; Thoe et al., 2014). Short-term bathing water quality (BWQ) provides simplified information to the public about how safe it is to bathe in particular bathing water in the next 24 h, however, does not reflect the real-time variations of bathing water quality and is not sufficient for an increasingly variable changing climate and growing risk of illness from use of bathing waters, which will require the prediction of changes that can be expected on a timescale of a few hours.

5 | HOW DO WE FORECAST BATHING WATER QUALITY?

Bathing water quality forecasts combine hydrometeorological forecasting, water quality, and ecological components. BWQ forecasts are based on the modeled relationship, for example, multiple linear regression analysis (MLR), between FIO (mainly IE) and multiple environmental variables including; meteorological conditions (precipitation, solar

FIGURE 2 "Excellent," "Good," "Sufficient," and "Poor" bathing water quality classification signage (Bathing water information and signage rules for local councils. Available at: https://www.gov.uk/guidance/bathing-water-information-and-signage-rules-for-local-councils).

radiation, air temperature, wind speed, and direction, dew point); water quality (turbidity, pH, conductivity/salinity, UV/visible spectra); hydrodynamic conditions (flow, magnitude, and direction of water currents, wave height, tidal stage); and other factors such as number of birds or bathers present (Table 2) (Kay et al., 2012; Stidson et al., 2012; Thoe et al., 2014, 2015; Tyrrell, 2017; USEPA, 2010). Methods to develop site-specific models incorporate statistical systems including standard and machine learning methods, deterministic systems, or combination of both (Grbčić et al., 2021; Gutiérrez et al., 2010; Searcy et al., 2018; Stidson et al., 2012; Tyrrell, 2017; USEPA, 2010). The most common model outputs are estimated levels of FIO or probability of exceedance of the set water quality standard (Stidson et al., 2012; Tyrrell, 2017; USEPA, 2010). Forecast models mostly use the rainfall forecast products available in a particular country to produce bathing water forecasts. The warning is issued when forecasted FIO (mainly IE and EC) thresholds are exceeded.

5.1 | Examples of operational systems

In England, forecasting of bathing water quality is managed by the Environment Agency (EA) via the National Pollution Risk Forecasting (PRF) system (Figure 3). Each bathing water has a unique set of environmental variables (e.g., rainfall, wind, UV light, time, tide, etc.), which are related to the IE concentrations. A Multiple Linear Regression (MLR) is used to find best-fitted variables, by successively adding explanatory variables while simultaneously removing the weakest correlated variables from the pool (Tyrrell, 2017). The result of MLR is a unique equation consisting of the best fitted variables for each bathing water, which is then exported to the Flood Early Warning System (FEWS) component of the EA's PRF system. FEWS is an operational forecasting platform developed by Deltares and used in over 40 operational centers worldwide. In England, it is currently used for several forecasting applications (Werner et al., 2013). The Incident Management Flood System (IMFS), embedded in FEWS, provides live forecast and observation data (rainfall data, UV index, wind speed, tide, time of the day, and month) for daily bathing water forecasts. Once all components required for bathing waters forecasting are transported to FEWS, they are exported and displayed on the government website https://environment.data.gov.uk/bwq/profiles/. If the water quality threshold is forecasted to be exceeded at any of the bathing waters, the forecasts are flagged by the Pollution Risk Messaging System (PRMS) and sent via SMS to registered beach operators informing them to display appropriate signage. PRMS also sends information to 33 nationwide electronic signs at beaches and generates a summary email sent to the Environment Agency for distribution (Tyrrell, 2017). The warning water quality threshold of 63 cfu/100 mL IE is calculated using the dose–response relationship and probability density function (Kay et al., 2005) for gastrointestinal illness using the microbiological data from Environment Agency England and Wales from 2000 to 2016 (Tyrrell, 2017).

Natural Resources Wales use a similar MLR approach to EA England. Key predictors used include rainfall, UV index, tide height, and wind speed/direction. The modeler and local bathing water specialist decide which model is chosen for each bathing water (Internal Report NRW). In Northern Ireland, statistical and machine-learning predictive models are combined, and their outputs are binary in that bathing waters are only classified as excellent or poor (Hawtree et al., 2020). In Scotland, rainfall and river flow were found to be strong predictors of high fecal contamination in bathing waters. For that reason, the forecasts work solely off rainfall and flow threshold triggers, which are site, gauge, and time-specific (Crowther et al., 2001; Crowther et al., 2003; Stidson et al., 2012). The models are calibrated to predict poor water quality at thresholds of 500 EC and/or 200 IE, in agreement with the percentile values specified in the rBWD. Table 2 provides examples of operational, pre-operational, and research only bathing water forecasting systems routinely using weather predictions as inputs.

5.2 | Limitations linked to statistical modeling and data collection

Due to the nonlinearity and complexity of the water environment (Figure 1) the exact microbial state of bathing waters is challenging to predict. No model has the capacity to predict all the factors, everywhere, all of the time, thus predictions of water quality status have limitations in skill and applications (Dickey-Collas et al., 2014). Forecasting tools designed based on past water quality and hydrometeorological data are limited by model parameterization, model-forcing data (e.g., precipitation forecasts), model input data (e.g., past water quality and bacteria levels), model validation data (e.g., use of incorrect thresholds, and scoring system), and model structures (e.g., use of different

TABLE 2 Examples of operational, pre-operational, and research-only bathing water forecasting systems.

Modeling approaches	Provider	No of forecasted BW	Factors used for forecasting	Warning trigger	Further information
Statistical based on MLR	Environment Agency England governmental agency, operational system (England)	415	Rainfall (radar), wind speed, wind offshore, wind alongshore, UV index, time day, time month, and tide height (maximum and minimum), past water quality results	IE threshold of 63 (cfu/100 mL)	Tyrrell (2017)
	Environment Agency Wales (Wales)		Rainfall radar, UV index, tide height, and wind speed/direction	IE threshold of 63 (cfu/100 mL)	(Internal report)
	Smart Coast Aberystwyth University and University College Dublin (Wales)	2	Rainfall, UV, and tide followed by wind speed, extra-terrestrial radiation (ETR), and river flows	Site dependent	Wyer et al. (2013)
Simple regression	SEPA-governmental agency, operational system (Scotland)	86	Rainfall triggers, river flow triggers, past water quality results	A single sample limit of 500 colony forming units (cfu) per 100 mL for Escherichia coli and 200 cfu/100 mL for IE	Stidson et al. (2012)
Decision trees	SEPA-governmental agency, tested method not operational (Scotland)	n/a	Flow, rainfall data, and past quality results	A single sample limit of 500 colony forming units (cfu) per 100 mL for Escherichia coli and 200 cfu/100 mL for IE	Stidson et al. (2012)
Combining statistical and deterministic systems: 3D real-time regional hydrodynamic and water quality model	The University of Hong Kong-Project WATERMAN purpose research only (China)	16	Rainfall, solar radiation, onshore wind, tide level	Beach closure criteria *E. coli* 610 counts/100 mL	http://www.waterman.hku.hk/
Statistical based on MLR and neural networks	Heal the Bay non-profit est, operational system US California (US)	25	Rainfall, wind speed/direction, pressure, cloud cover, air temperature, water temperature, dew point, tide range/min/max, wave height/period, flow, past FIOs concentrations	FIOs concentrations exceed their single sample standard (SSS): 10,000, 400, and 104 most probable number (MPN)/100 mL for TC, FC, and IE, respectively	Searcy et al. (2018); Thoe et al. (2014, 2015)
Combining statistical and machine-learning predictive models	EU SWIM Project (Northern Ireland)	9	Wind direction, wind speed, atmospheric pressure, air temperature direct normal irradiance, tides, streamflow, rain radar	Binary output, bathing waters classified as excellent or poor	Hawtree et al. (2020)

(Continues)

TABLE 2 (Continued)

Modeling approaches	Provider	No of forecasted BW	Factors used for forecasting	Warning trigger	Further information
Combining statistical and deterministic	COWAMA by CLABSA and the Barcelona's City Council (Spain)	1	Fed with real-time rainfall data from controlled sensors and meteorological model predictions	The procedure is characterized by the definition of risk levels from 0 to 5, depending on the severity of the pollution event and the available information as the event develops	Gutiérrez et al. (2010)

Note: FIO: TC (total coliform), FC (fecal coliform), or EI (enterococcus).

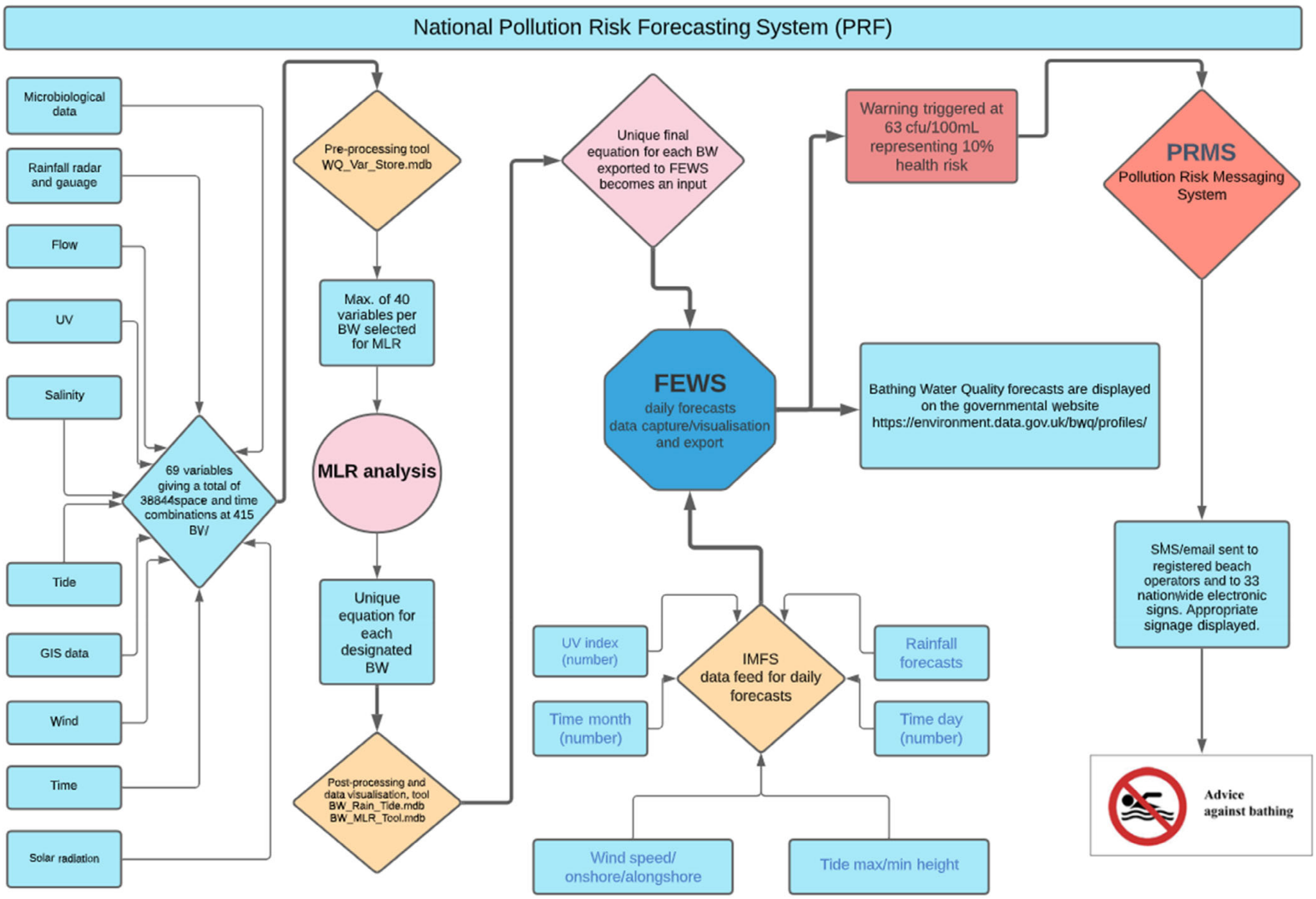

FIGURE 3 National pollution risk forecasting system (PRF) for England.

mathematical representations). Consideration of these uncertainties is vital for the model application and for the interpretation of obtained results (Schellart et al., 2010).

The most limiting factor is the fact that operational models use low-frequency data collected for legal compliance, meaning that sampled data is close to where the model predicted it would be and data representing extreme conditions are not collected. This approach does not reflect the science behind the environmental fate of FIO (Herrig et al., 2019; Shutler et al., 2015; WHO, 2003). Since most water quality exceedances are single-day or hourly events, the chance of capturing the elevated levels of IE is exceptionally low (5%) (Leecaster & Weisberg, 2001). This may create the false idea that failures happen rarely in the bathing season (Crowther et al., 2001; Hatvani et al., 2018; Lušić et al., 2017; Wyer et al., 2018). If bathing water rarely has high bacteria levels and events are not captured, the statistical significance would be too low to develop a model (Hampson et al., 2010; Tyrrell, 2017; USEPA, 2010). For that reason, there are 415 designated bathing waters in England, however, daily forecasts are only issued for around 170 because models for the other locations perform too poorly (Tyrrell, 2017).

What is more, the classification samples do not consider temporal and spatial variability in FIO density, which may change over minutes and hours within the bathing day (Bedri et al., 2016; Boehm et al., 2002; Layton et al., 2009; Wyer et al., 2018). Indicator bacteria are sensitive to sunlight; therefore, the time of day when samples are collected may significantly influence the final enumeration results (Hijnen et al., 2006; Pullerits et al., 2020). The spatial distribution of microbial pollution depends also on their susceptibility to salinity, DO, turbidity, CSOs discharge patterns, location of sources of pollutants, advection, and the distribution of mixing on the site (Alkhalidi et al., 2021; Cherif et al., 2019; Poopipattana et al., 2021). In general, the highest values of bacteria and the poorest water quality according to in situ measurements are recorded next to the river mouth, while lower values and better water quality status are observed moving away from the confluence of the river mouth with the sea (Cherif et al., 2019). FIO concentrations tend to vary less in deeper waters than in shallower zones (e.g., >45 cm) due to resuspension of FIO growing or sheltered in sediments (Whitman & Nevers, 2008). Additionally, correlations between indicator FIO concentrations measured at that depth tend to have better correlations with gastrointestinal infection incidence rates (USEPA, 2012). This situation also further lowers variance (based on r^2 alone), which could lead to misclassification of "sufficient" water quality when it was in fact "poor" (Wyer et al., 2018). In practice, it can also lead to clean beaches being closed and beaches at which contamination occurred being open for public use (WHO, 2003).

5.3 | Rainfall forecasts used in BWQ forecasts in England

Bathing water quality forecasts in England are driven by rainfall forecasts (Figure 3) provided by the UK Met Office, including rainfall radar products, nowcast, and UKV (United Kingdom Variable-resolution weather forecasting system) short-range forecasts (Tang et al., 2013) (Figure 4). A nowcast is a weather forecast on a very short-range period 0–6 h, which uses surface weather station data (e.g., rain gauge, radar) blended with Numerical Weather Predictions (NWP) models, with updates available every 15 min (Liguori & Rico-Ramirez, 2014). NWP uses initial conditions of the state of the atmosphere, land surface, and oceans, and then forecasts future weather using numerical equations and parameterizations of physical processes over a specified domain (geographic area) (Pu & Kalnay, 2018). The UK Met Office short-

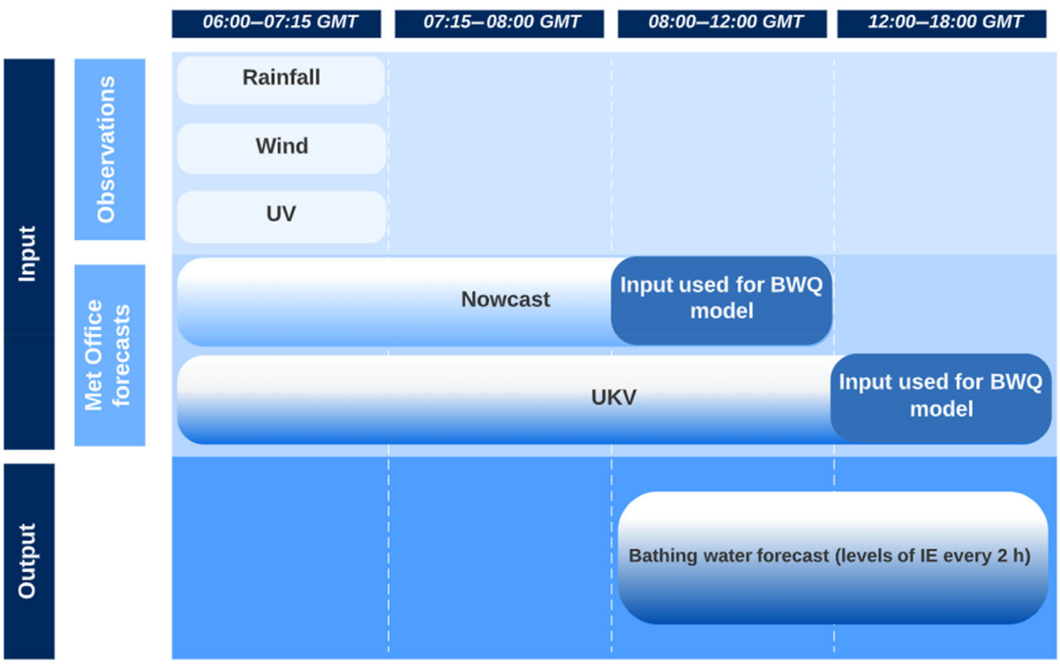

FIGURE 4 Timing and sequence of observations and forecasts that are input into the Environment Agency bathing water quality forecast.

range UKV model, provides forecasts on a 1.5-km grid across the United Kingdom for up to 120 h lead time (5 days ahead) with frequent updates for up to 54 h ahead. The nowcast blends radar products with the UKV which dominates from 3 h ahead. In the short term (up to 6 h) nowcasting is preferred for bathing water forecasting as it has better skill in representing rainfall at short lead times (Prudden et al., 2020).

All observed and forecasted data are input into the bathing water forecasting system and then merged into one product before the MLR variables are calculated (Tyrrell, 2017). Rainfall radar observations and data from nowcast and UKV are inputted at 06:00 GMT. The wind and UV data is imported at 07:15 GMT. The forecasted values for IE in 2 h step time from 09:00 to 16:00 GMT are then averaged. The warning is issued when the calculated average is 63 cfu/100 L or above. The daily bathing water quality forecast is given to beach operators between 8:00 and 8:30 GMT. The bathing water forecast is not updated throughout the day.

6 | HOW CAN WE IMPROVE STATISTICAL MODELING PERFORMANCE BY IMPROVING SAMPLING REGIMES?

The low statistical probability of extreme events forces the need for a substantial set of data to analyze predictions with more statistical rigor. Additionally, the assumption of characterizing the bathing day based on few spot samples taken at random times might not fully characterize important conditions and the exact reasons for non-compliance, which is so important to allow appropriate remediation measures to be put in place (Cyterski et al., 2013; Stidson et al., 2012; Thoe et al., 2014; USEPA, 2012). Site specific sampling regimes, especially in instances where the model performance is poor, would allow a much better characterization of the standard deviation and variances, leading ultimately to better model outcomes (Bedri et al., 2016; Kay et al., 2012, 2018; Wyer et al., 2018). For example, the Smart Coast project designed for Swansea Bay to sample FIOs at half hourly intervals for 12:00 h of the bathing day (i.e., 25 samples/day), over 60 days of the bathing season, led to more accurate forecasting of IE levels in Swansea Bay. A cost-effective way of checking whether the number of exceeded compliance samples is sufficient for model development would be application of internal validation of models by bootstrapping or cross-validation (Motamarri & Boccelli, 2012; Searcy et al., 2018). To represent temporal and spatial variability, the USEPA (2010; 2012) suggested compliance monitoring of bathing waters should focus on early morning sampling to produce a preventive approach to health risk management. However, regulatory monitoring in the United Kingdom is carried out throughout the day, because the sampler has several beaches to visit each day, therefore such a suggestion is not practical and would substantially increase the cost of monitoring. In this instance health risk predictions might be improved by investing time and resources in more adequate modeling of within-day patterns obtained from targeted monitoring and observed data (Wyer et al., 2018).

Water sample results are the primary source of information about levels of bacteria during different environmental conditions. The available historical raw bacteria levels data, although known to be incomplete, underpin our understanding of key processes, particularly the impact of rainfall on bacteria levels in coastal waters. Without historical water sample data, it would be impossible to draw any firm conclusion on relationships between bacteria levels and environmental conditions. BWQ forecasts are based on the modeled relationship between bacteria and environmental conditions, therefore it is vital to improve our scientific understanding of the impacts of environmental conditions on bacteria levels in coastal environments and well as monitor changes over time that may be rated to climate change. Targeted sampling regimes for the collection of IE/EC data reflecting extreme events would also provide foundations for a better forecasting approach to be used for bathing waters forecasting. Many major bathing water pollution events are not adequately measured, and pre-scheduled compliance sampling regimes are a stumbling block in addressing this problem. Thus, currently, some bathing waters do not have enough independent extreme events for meaningful and robust analysis of impacts of intense rainfall on bacteria levels in coastal waters.

Our incomplete understanding of the physical processes driving the levels of bacteria in coastal waters, and the inadequate record water samples make it a challenge to forecast bathing water quality accurately.

Collecting one robust set of data for one bathing water does not mean we would be able to apply it to other bathing waters because of spatial and temporal non-stationarity, that is, each catchment and receiving bathing water is unique, as are the driving storm characteristics, and the characteristics of the mobilized pollutants, means that bathing water pollution events cannot be easily compared with one another, even at the same location. Changing precipitation patterns because of climate change, together with human alteration of catchments exacerbates this problem. This underlines the need for targeted sampling regimes tailored specifically for a particular bathing water to build up the dataset so that relationships between bacteria levels and intense rainfall can be better understood.

7 | HOW CAN WE IMPROVE BATHING WATER FORECASTING USING ADVANCES IN FORECASTING SCIENCE?

Convective rainfall develops quickly and is therefore difficult to forecast accurately. It is challenging to forecast convective events because it involves multiple physical processes, many of which occur at scales smaller than a model grid cell. Additionally, lack of data at high spatial and temporal scales means that some processes remain poorly understood (Kendon et al., 2018; Kent et al., 2022; Ravuri et al., 2021).

7.1 | Advances in rainfall observations and how they can improve bathing water forecasts?

Rainfall observations can serve two purposes: directly contributing to the bathing water forecasting system or providing initial conditions to enhance precipitation forecasts. When it comes to bathing water forecasting, a significant challenge in using rain gauge data is ensuring a sufficiently dense spatial coverage of gauges to capture intense rainfall in localized areas. It is recommended to have a gauge density of one per 1 km^2 for accurate hydrological modeling and forecasting (Liguori & Rico-Ramirez, 2014; Ochoa-Rodriguez et al., 2019). The current rain gauge network in the United Kingdom is inadequate for this purpose (Speight et al., 2021).

Rainfall radar offers distinct advantages compared with rainfall gauges. Radar has the capability to survey large areas, capturing the spatial variability of rainfall. Additionally, radar provides real-time data and can determine the motion, intensity, and type of precipitation (Battaglia et al., 2020; Garcia-Benadí et al., 2021). The use of modern dual-polarization radars (Adams et al., 2016), allows for the capture and processing of additional information regarding the size and composition of precipitation (Dance et al., 2019; Flack et al., 2019). Improvements in radar-observed rainfall rates, which are fundamental for accurate forecasting and nowcasting, also enabled better forecasting of intense rainfall events and enhanced flood warning systems (Deng et al., 2014; Wang et al., 2021). Despite these advancements, rainfall radar technology cannot guarantee accurate capture of high intensities and local conditions, fundamental for accurate bathing water quality forecasting. This is because dynamical microphysical attributes between convective and stratiform precipitation differ significantly (Deng et al., 2014). In the future poor radar coverage and lack of ground gauging stations may be able to be enhanced with satellite products. However, at present these are mostly only useful for larger-scale weather patterns and climatic investigations, and are unable to pick up the localized and intense nature of rainfall-based processes (Agyekum et al., 2023; Houngnibo et al., 2023).

With a denser rain gauge network and more sophisticated radar and satellite technology, rainfall forecasters would be able to obtain more precise and timely information about convective rainfall intensity and location, feeding this information to bathing water forecasters and improving the bathing water forecast output. This would enable events to be tracked that may lead to increased runoff and potential contamination of bathing water on a local scale in space and time, allowing timely warnings or advisories to beach managers and the public, helping to mitigate potential health risks. Advances in rainfall observations would also be able to provide valuable data for hydrological models, which form the basis of many operational systems simulating the movement of water and pollutants in the environment. Thus, by enhancing observational rainfall data accuracy, we would be able to generate more reliable models that form the backbone of operational bathing water quality systems and improve predictions of pollutant transport and its impact on bathing water quality. This ultimately would increase the safety and quality of bathing water for the public.

7.2 | Advances in nowcasting and numerical weather prediction and how they may improve the existing approach

Bathing water quality forecasts in England are driven by nowcast and NWP rainfall forecasts (Figure 4). Nowcasts are unable to provide precise predictions for longer lead times, and often have low skill in predicting medium-to-heavy rainfall events accurately (Ravuri et al., 2021). For this reason, NWP models are blended with nowcasts to provide longer lead times 6–72 h (Chen et al., 2023, Kendon et al., 2023).

Traditional nowcasting methods primarily rely on extrapolating radar echo maps or satellite images. These methods involve identifying storms, tracking, and extrapolating their movement, or estimating the flow field. While these methods are effective in predicting the short-term linear advection characteristics of storms, they face limitations in forecasting the initiation and evolution of convective storms, particularly when the lead time exceeds 30 min (Ravuri et al., 2021). Research has shown that these extrapolation-based methods struggle to accurately predict the development of convective storms for longer lead times (Dixon & Wiener, 1993; Gultepe & Feltz, 2019; Wilson et al., 1998). Machine learning has potential to overcome some of the shortcomings with regards to convective rainfall forecast accuracy (see Section 7.4); however, more research is needed to apply the findings to existing operational systems in the United Kingdom. Although nowcasting still has limitations, especially when it comes to the accuracy of convective rainfall forecasting, it may enhance bathing water forecasting by providing real-time data analysis of local conditions, enabling authorities to provide more precise and localized predictions and recommendations for beach users, ensuring their safety (Clark et al., 2016; Dance et al., 2019; Weusthoff et al., 2010). The challenge of representing convection in NWP forecasting models is important because it influences the skill of bathing water forecasts. Recent advances in convection-permitting NWP models (CPMs) have improved the representation of convective rainfall structures and processes (Kendon et al., 2023, Kent et al., 2022). These have been shown to outperform large-scale models that rely on some form of convection parameterization process which relates the convection process to the rainfall using a statistical approach (Park et al, 2022; Yang ben et al., 2022). For example, the UK Met Office UKV model can represent convective structures directly producing realistic-looking shower cells (Milan et al., 2020). Since skillful forecasts of convective rainfall from UKV are updated hourly, they should be used in current operational bathing water forecasting systems and sub-daily updates could be provided to the public.

Although the 1.5 km grid enables realistic showers to be generated the chaotic nature of atmosphere imposes a significant limitation on the skill of rainfall precipitation forecasting meaning it remains difficult to forecast convective rainfall for specific locations beyond a few hours ahead creating challenges for decision makers (Speight et al., 2021). To mitigate these limitations meteorologists are incorporating more precise and complex observational data, improving computational capabilities, and refining the physical parametrization of NWP models. A flexible system that can incorporate improvements to rainfall forecasts as and when they become operational is key to keep pace with recent developments in forecasting science. Additionally, ensemble forecasting techniques are used to account for uncertainties and to indicate the likelihood of different weather scenarios.

7.3 | Ensemble prediction systems and how they can improve bathing water forecasts

Although convective rainfall develops over small areas quickly, it depends on atmospheric conditions controlled by large-scale or local factors (Flack et al., 2019). Therefore, a probabilistic (ensemble) approach is required to take account of the uncertainties, mostly associated with the initial conditions, boundary conditions, as well as physical processes (Hagelin et al., 2017). An ensemble forecast is a set of forecasts that present the range of possible future weather outcomes. Multiple simulations are run, each with a slight variation of the initial atmospheric state to represent different rainfall scenarios (Cloke & Pappenberger, 2009). Using ensemble would generate a range of possible outcomes of bathing water quality, showing how likely different scenarios are in the days ahead, and how long into the future the bathing waters forecasts are useful (ECMWF, 2020). For example, the Short-Term Ensemble Prediction System (STEPS) is a probabilistic precipitation nowcasting scheme developed at the Australian Bureau of Meteorology in collaboration with the UK Met Office. STEPS downscales the NWP forecast model allowing small scales to be represented. Consequently, the scheme has better skill in representing the distribution of precipitation rate at spatial scales finer than those adequately resolved by operational NWP (Bowler et al., 2006).

Currently, the Met Office convective-scale ensemble for numerical weather prediction, for the Met Office Global and Regional Ensemble Prediction System over the United Kingdom, called MOGREPS-UK, uses an hourly time-lagged configuration to take advantage of the hourly 4D-Var data assimilation run in the deterministic UK model with variable horizontal resolution, the UKV (Porson et al., 2020). This operational ensemble prediction system has been successful in capturing organized convection but may be insufficient to capture the convection process that results in convective precipitation (Clark et al., 2016). The strength of MOGREPS-UK is that it can provide an indication of the possibility of convection-driven events and total rainfall prediction, however, exact intensity or localization remains a challenge (Porson et al., 2020). Understanding these limitations will help assess realistic forecast skills and improve operational decision-making processes in different weather circumstances, especially when it comes to impact assessment of convective rainfall on bathing water quality. To realize the full potential of probabilistic forecasts (advance the ensemble size, resolution, domain size, and forecast length) more computational power would be needed (Cloke & Pappenberger, 2009; Speight et al., 2021). As computational power increases it will be possible to further increase the ensemble size, resolution, domain size, and forecast length of ensemble forecasts. Recently alternatives such as time-lagging (Porson et al., 2020) have been successfully shown to increase ensemble size without increasing computational burden. Machine learning approaches could have an advantage as they may remove the computational burden of running forecasts or post-processing ensembles (Gibson et al., 2021; Zhang et al., 2023).

Currently bathing water forecasts in the United Kingdom are only updated daily and ensembles are not used, therefore bathing water forecasts are not making best use of available weather forecasting science. Similar challenges have been experienced in the field of flood forecasting, particularly for surface water flood events (Speight et al., 2021), and bathing water forecasting would benefit from learning from parallel developments in the use of convective permitting forecasts by hydrometeorologists.

7.4 | Advances in machine learning

Advances in machine learning combined with physically based meteorological and hydrological models offer exciting potential for improving the predictive skill of a range of hydroclimatic events including bathing water failures (Slater et al., 2023). Machine learning algorithms in forecasting refer to the use of statistical models and algorithms that allow computers to learn and improve from data without explicit programming. These algorithms analyze historical data and patterns to identify relationships and make predictions about future outcomes (Krenn et al., 2022). Machine learning can effectively blend data from multiple sources, such as NWP, radar observations, satellite imagery, and ground-based measurements to produce more accurate convective rainfall forecasts (Hess & Boers 2022; Prudden et al., 2020; Schultz et al., 2021), which would enable more accurate bathing water forecasts. By handling vast amounts of historical weather data, machine learning algorithms can identify complex relationships and can effectively capture the nonlinear dynamics of weather patterns that contribute to convective rainfall events. This enables more accurate predictions and improved understanding of the complex dynamic physical processes involved in convective rainfall (Caseri et al., 2022; Gibson et al., 2021; Huntingford et al., 2019).

Machine learning models can also adapt and learn from new data, allowing them to continuously improve their forecasting capabilities and enhance the accuracy and reliability of convective rainfall forecasts over time (Ghada et al., 2022; Ravuri et al., 2021).

Nowcasting powered by machine learning and data assimilation techniques, can incorporate real-time data from various sources to provide more accurate rainfall forecasts (Prudden et al., 2020). By detecting anomalies or patterns indicating a higher risk of convective rainfall occurrence, nowcasting models enable authorities to proactively issue warnings and implement mitigation strategies to protect the public (Ravuri et al., 2021). Machine learning models can adapt and update their predictions as new data becomes available, ensuring that both rainfall forecasts and bathing water forecasts remain accurate and reliable even in the face of changing conditions such as sudden weather changes or pollution incidents. This highlights why improvements in observational data are so important.

Machine learning algorithms can quantify and handle uncertainties by providing probabilistic forecasts, allowing decision-makers to assess the confidence level associated with a forecast and make informed decisions based on the level of uncertainty (Abdar et al., 2021; Jose Dinu et al., 2022).

Similar to improvements in convective rainfall forecasts, machine learning algorithms could incorporate historical water quality data, weather conditions, tidal patterns, and pollution sources identifying correlations and patterns that may affect bathing water quality. Machine learning algorithms could help build predictive models based on historical data and environmental factors to forecast bathing water quality, particularly if better in situ water quality data were available. Machine learning could potentially be used to develop early warning systems for bathing water quality independently from existing modeling systems. By analyzing historical data and identifying patterns associated with water contamination events, machine learning models could provide alerts and recommendations to beach managers and authorities, enabling them to take proactive measures to maintain water safety.

Machine learning could also provide insights and recommendations on actions to improve water quality, such as identifying pollution sources or suggesting upgraded beach management strategies. Machine learning models, however, are only as good as the data they are trained on. Ensuring the quality and representativeness of the training data, as well as addressing potential biases, are crucial steps in developing accurate and reliable bathing water forecasting models.

While machine learning has shown promising results in convective rainfall forecasting, it is not without its challenges and is unlikely to be able to resolve all of the complexities and chaotic functions of the atmosphere. Ensuring the quality and representativeness of the training data, addressing biases, and interpreting the outputs of complex models are ongoing areas of research and development.

8 | CONCLUSIONS

Forecasting bathing water quality is essential to keep beach users safe, yet the current system in (England) can be much improved. Sampling strategies can be improved by targeting intense rainfall conditions, that would allow better understanding of extreme rainfall impact on bathing water pollution. This in turn would improve the skill of statistical modeling leading to more accurate bathing water forecasts. Since bathing water forecasts rely mostly on efficient and accurate rainfall forecasts, a significant improvement would be using the currently available sub-daily short-range rainfall forecasts to provide sub-daily bathing water forecasts that more closely reflect the dynamic development of convective rainfall events. Sub-daily forecasts would help with gaining experience of predicting the impact of convective rainfall on bathing waters which would contribute to the longer-term development of a system that better predicts localized pollution events. Ongoing development of machine learning in weather forecasting, nowcasting, and bathing water quality modeling offers potential to provide better early warnings of bathing water failures to aid real-time, dynamic, site-specific forecasts, and warnings that will improve operational logistic planning and decrease the risk to public, but such developments remain contingent on the availability of appropriate training data.

While metrological models and computational power have significantly improved over the years, there are still inherent limitations in predicting the non-linear (chaotic) dynamics of the atmosphere. Complex interactions and feedback loops within the atmosphere lead to uncertainties in forecasts making precise forecasting challenging.

To further upgrade bathing water forecasting, the BW forecast should move toward ensemble prediction systems which represents the latest advances in weather forecasting science and allows decision-makers to take account of this forecast uncertainty. To make effective use of ensemble forecasts bathing water forecasters would need to consider probabilistic decision making which has not been considered to date in bathing water forecasting. Probabilistic forecasts can give an earlier indication of potential upcoming bathing water failures and associated impacts by showing the probability of exceeding given thresholds, extending the amount of time available to prepare. However, this is only effective when an existing framework for using probabilistic forecasts within the decision-making process exists (Arnal et al., 2020). Once established, the probabilistic approach can be cascaded to be used by BWQ forecasters and water quality specialists. However, this requires a clear channel of communication between weather forecasters and bathing water forecasters to be established. There is a need for specific guidelines for establishing appropriate thresholds, explaining how the probabilistic forecasts should be used in practice in combination with other systems operating in the EA. Also, clear communication with all internal and external stakeholders should take place explaining advantages of probabilistic forecasting over deterministic forecasting.

The demand for rapid and accurate bathing water quality forecast information in support of critical decision-making will grow fast in the coming years due to climate change and resulting changes in precipitation patterns and user demand. The current operational bathing water services worldwide and in the United Kingdom have limited capability. To fully embrace recent advances in digital and forecasting technologies and to deliver a new bathing water forecasting structure that provides seamless services, five main challenges need to be addressed.

8.1 | Key challenge 1: Improve monitoring of bathing waters

The most suitable predictors for bathing water quality are location-dependent and compliance data might not be comprehensive enough to develop a model for a BW. This can be improved by targeted monitoring of bathing waters focusing on sampling spatial and temporal characteristics as well as frequency. Targeted data sets would provide better data to develop predictive models, thus improving the accuracy of bathing water forecasts.

8.2 | Key challenge 2: Better use of existing very short and short-range forecasts

Climate change models suggest that the most severe bathing water failures could result from rapidly developing convective systems with storm cells producing intense rain and runoff. Bathing water forecasts do not take full advantages of available nowcasting science. Taking full advantage of nowcasts and short-range forecasts would allow an update of the BWQ forecast during the day to take account of rapidly developing storms, that may not have been shown in the morning nowcasts, allowing the development of sub-daily BWQ forecasts. As nowcasting accuracy increases it will be possible to further increase the accuracy of BWQ forecasts.

8.3 | Key challenge 3: Moving toward an ensemble prediction system for bathing water forecasts

Currently, forecasting of bathing water quality beyond 24 h is not possible without significantly compromising accuracy, especially when considering convective rainfall events. Convection-permitting NWP models can represent convective structures and can now forecast showers (Clark et al., 2016). Still due to the localized nature of convective events, NWP models need further improvement to be able to forecast the location of the heaviest rainfall on a small catchments scale, which is vital for accurate bathing waters forecasting. Ensembles provide information on forecast uncertainty. Using ensembles would enable the creation of different possible outcomes of bathing water quality in the days ahead and it would also inform decision makers how long into the future the bathing waters forecasts are useful. However, probabilistic forecasts have not been yet used in bathing water quality forecasting and this creates a lack of understanding of what actions people might take several days ahead. Additionally, a new threshold system of pollution and its probable impact on health would need to be established, merging the hazard and impact probabilities into one risk-based message.

8.4 | Key challenge 4: Developing interdisciplinary solutions

To effectively manage bathing waters forecasts, it is crucial for hydrologists and meteorologists to collaborate and communicate a consistent message, especially when faced with short lead times. This collaboration should prioritize understanding the needs of decision-makers while maintaining the expertise of hydrometeorology at the core of the solution. Key issues, such as determining the useful lead time, identifying forecast probabilities that trigger action, and assessing the value of focusing on impact rather than hazard, require input from all stakeholders involved in the forecasting process (scientists, operational end-users, hydrologists, meteorologists, social scientists) during the initial stages of system development. A strong collaboration between forecast developers and beach users would need to be established. This would enable the creation of a forecast product that effectively meets operational requirements and is smoothly transitioned from research to an operational system. Likewise, it is important for academic scientists to actively engage with stakeholders to ensure that their scientific work addresses practical needs in the real world.

8.5 | Key challenge 5: Secure appropriate funding

High-quality bathing water forecasting is essential for providing timely and accurate information to the public, to warn them, to help them make informed choices, and to avoid health implications associated with poor bathing water quality. Despite this, it is not valued and recognized by organizations and beach users due to poor and sparse environmental data, outdated technological and science approaches, and opinions driven by political agendas. Adapting to the changing climate calls for immediate improvements in our current forecasting approach. The establishment of new funding streams will require time, effective engagement with stakeholders, and consideration of the challenges ahead.

If we are to reduce the risk from poor bathing water quality and avoid the increasing number of beachgoers reporting being ill after being diagnosed with EC poisoning, then we should endeavor to meet these challenges quickly and take advantage of recent scientific advances in forecasting. Considering the possibility of worsening bathing water quality due to our changing climate, addressing shortcomings in current bathing water forecasting operational practice should be a priority for government to keep our bathing water clean and people safe.

AUTHOR CONTRIBUTIONS

Karolina Urszula Krupska: Conceptualization (lead); data curation (lead); formal analysis (lead); funding acquisition (lead); investigation (lead); methodology (lead); project administration (lead); resources (lead); software (lead);

validation (lead); visualization (lead); writing – original draft (lead); writing – review and editing (lead). **Linda Speight:** Conceptualization (supporting); data curation (supporting); formal analysis (supporting); funding acquisition (supporting); investigation (supporting); methodology (supporting); project administration (supporting); resources (supporting); software (supporting); supervision (supporting); validation (supporting); visualization (supporting); writing – original draft (supporting); writing – review and editing (supporting). **James Stephen Robinson:** Conceptualization (supporting); data curation (supporting); formal analysis (supporting); funding acquisition (supporting); investigation (supporting); methodology (supporting); project administration (supporting); resources (supporting); software (supporting); supervision (supporting); validation (supporting); visualization (supporting); writing – original draft (supporting); writing – review and editing (supporting). **Adam James Gilbert:** Conceptualization (supporting); data curation (supporting); formal analysis (supporting); funding acquisition (supporting); investigation (supporting); methodology (supporting); project administration (supporting); resources (supporting); software (supporting); supervision (supporting); validation (supporting); visualization (supporting); writing – original draft (supporting); writing – review and editing (supporting). **Hannah Cloke:** Conceptualization (supporting); data curation (supporting); formal analysis (supporting); funding acquisition (supporting); investigation (supporting); methodology (supporting); project administration (supporting); resources (supporting); software (supporting); supervision (lead); validation (supporting); visualization (supporting); writing – original draft (supporting); writing – review and editing (supporting).

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CONFLICT OF INTEREST STATEMENT

Karolina Krupska worked for the Environment Agency between 2012 and 2023. Adam Gilbert currently works for the Environment Agency and has done so since 1997. The remaining authors have declared no conflicts of interest for this article.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

RELATED WIREs ARTICLES

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