Predictive Tools for Beach Notification Volume I: Review and Technical Protocol

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Abbreviations and Acronyms

AIC	Akaike's Information Criterion
ANN	artificial neural network
BEACH Act	Beaches Environmental Assessment and Coastal Health Act
BIC	Bayes Information Criterion
CART	classification and regression tree
CFU	colony forming units
cm	centimeters
CSO	combined sewer overflow
DNA	deoxyribonucleic acid
DO	dissolved oxygen
E. coli	*Escherichia coli*
EFDC	Environmental Fluid Dynamics Code
EMPACT	Environmental Monitoring for Public Access and Community Tracking
EPA	U.S. Environmental Protection Agency
GLERL	Great Lakes Environmental Research Laboratory
FIB	fecal indicator bacteria
HSPF	Hydrological Simulation Program—Fortran
in	inches
mL	milliliters
NOAA	National Oceanic and Atmospheric Administration
NWS	National Weather Service
POTW	publicly owned treatment works
qPCR	quantitative Polymerase Chain Reaction
R^2	coefficient of determination
ROC	Receiver Operating Characteristic
RTI	Research Triangle Institute
S.A.F.E.	Swimming Advisory Forecast Estimate

SMTM	Simple Mixing and Transport Model
SSO	sanitary sewer overflow
SWMM	Storm Water Management Model
TPM	Tidal Prism Model
USGS	U.S. Geological Survey
UV	ultraviolet
WWTP	wastewater treatment plant

Executive Summary

The U.S. Environmental Protection Agency (EPA) is in the process of developing new or revised recreational water quality criteria as required in the Beaches Environmental Assessment and Coastal Health Act (BEACH Act) of 2000. As part of that process, EPA is investigating a faster method of analysis of fecal indicator bacteria (FIB) in a series of epidemiology studies. Such a rapid method would provide analytical results in 4–6 hours, which does not include transportation time to the laboratory or laboratory preparation time. Even with the rapid method, results might not be available on the same morning samples are collected or even on the same day. One means to supplement, not replace, analytical results and to make same-day public health decisions is to use predictive tools such as statistical models, rainfall threshold levels, and notification protocols.

This document is Volume I of a two-volume report. Volume I summarizes current uses of predictive tools to provide model developers with the basic concepts for developing predictive tools for same-day beach notifications at coastal marine, Great Lakes, and inland waters.

Volume II provides results of research conducted by EPA on developing statistical models at research sites. It also presents Virtual Beach—a software package designed to build statistical multivariable linear regression predictive models.

The types of predictive tools that can be used to make beach notification decisions fall into the following categories—statistical regression models, rainfall-based notifications, decision trees or notification protocol, deterministic models, and combinations of tools.

- A statistical model (also called a statistically based model or a *predictive model*) is a general term for any type of statistical modeling approach to predicting beach water quality. A statistical correlation is observed between FIB and environmental and water quality variables that are easier to measure than FIB. Typical variables include meteorological conditions (solar radiation, air temperature, precipitation, wind speed and direction, and dew point); water quality (turbidity, pH, conductivity/salinity, and ultraviolet (UV)/visible spectra); and hydrodynamic conditions (flows of nearby tributaries, magnitude and direction of water currents, wave height, and tidal stage).
- A rain threshold level is another predictive tool used in many locations as the basis for a beach notification. Many beach managers have noticed a connection between the concentration of FIB at a beach and the amount of rain received in nearby areas. That relationship can be quantified as an amount or intensity of rainfall (a threshold level) that is likely to cause exceedances of water quality standards at a beach, and the length of time over which the standards will be exceeded.
- Beach managers can also develop a series of questions or a decision tree, considering factors such as rainfall, to guide beach notifications. Such evaluations use water quality sampling, rainfall data, and other environmental factors that could influence the FIB levels (such as proximity to pollution sources, wind direction, visual observations, or

other information specific to the region or beach). In this document, that process is referred to as developing a notification protocol.

Developing a basic understanding of the regional hydrology can be an important part of developing and using a predictive tool. This report addresses the influence of different hydrologic settings and how they affect the development of a predictive tool.

This document presents predictive tools that health departments and other responsible agencies are using for predicting water quality conditions and making timely decisions on beach notifications. An overview and a short description are presented for each predictive tool for which information was available. The document presents details on the elements required for developing a statistical model, according to a review of available literature. It discusses techniques for refining models and advanced statistical methodologies. The document also outlines general procedures for developing rainfall threshold levels and notification protocols.

A review of predictive tools for beach notifications reveals different challenges for each beach. Developing a predictive tool requires a commitment of resources (data collection, computer software, expertise), but there is no guarantee that a useful predictive tool will be produced. The applicability and challenges of predictive tools are discussed.

Finally, the document discusses future directions that EPA considers likely for predictive tools for beach notifications. Reliably forecasting beach water quality conditions a day or more in the future, related to weather forecasting, is a next step. Attempts are being made to develop models that apply to more than one beach or to a region of shoreline.

1 Document Overview and Background

Document Overview

This document is Volume I of a two-volume report. The goal of this document is to provide beach managers and developers of predictive tools with technical protocol for developing predictive tools for same-day beach notifications at coastal marine, Great Lakes, and inland waters. The technical protocol, or specific directions for developing predictive tools for beach advisories, is in Chapters 5 and 6. The background section below provides background information on the BEACH Act, beach monitoring, water quality criteria, analytical methods, and previously used beach predictive tools. Chapter 2 describes basic types of predictive tools used for making timely beach advisory decisions. Chapter 3 discusses the influence that different hydrologic environments have on beaches and how they affect model development. Chapter 4 summarizes current uses of predictive tools in predicting water quality exceedances at beaches. Chapter 5 provides technical protocol for developing statistical models, and Chapter 6 provides technical protocol for developing rain threshold levels for beach advisory decisions. Chapter 7 reviews the applicability of predictive tools, and Chapter 8 discusses trends that EPA sees in predictive tools for beach notifications.

Volume II of this report describes site-specific applications of statistical models to several beach environments and analyses of results. Volume II also presents Virtual Beach, a software tool designed to build statistical multivariable linear regression predictive models at beaches.

Background

Coastal, Great Lakes, and inland beaches are treasured natural resources that provide significant value, including recreational benefits. Those benefits are challenged by regular input of pollutants from point and nonpoint sources. Recreational activities are especially affected if fecal matter, treated or untreated, originating from human and animal sources is in the water. Ingesting polluted waters or other exposure, resulting from recreational uses, can lead to illnesses such as gastroenteritis, fever, hepatitis, and cryptosporidiosis, as well as infections of the skin, ears, and respiratory system (USEPA 2002).

The BEACH Act was passed in October 2000 to reduce the human health risks associated with water contact at coastal and Great Lakes beaches. The act requires EPA to coordinate and provide grant funds to support water quality monitoring and beach notification programs in states, territories, and eligible tribes with coastal or Great Lakes recreational waters. The program goals consist of informing the public of water quality problems at beaches (through notices that either provide advice about beach usage or close beaches), identifying sources of pollution, investing in analytical methods development, and improving water quality at beaches.

The terms *indicator bacteria*, *bacteria*, and *indicators* all refer to FIB whose presence in recreational water signal the presence of fecal material and any pathogens it might contain.

FIB are associated with disease-causing pathogens and are detected through sample collection and laboratory analysis. Culture-based, analytical methods for quantifying FIB included in EPA’s 1986 recreational water quality criteria commonly take 24–48 hours to provide results. Those culture methods have been improved to 18–48 hours (depending on the method and the bacteria being detected). In the time between sampling and public notification of the sampling results, swimmers can be exposed to pathogens through activity in the water. Information used to issue closure notification today is often based on yesterday's sample data. Conversely, elevated indicator densities detected in today's sample might no longer be present when the analytical results are received, resulting in unnecessary closure and an unjustified adverse economic effect.

EPA is in the process of revising the Recreational Ambient Water Quality Criteria as required in the BEACH Act of 2000. As part of that process, the quantitative polymerase chain reaction (qPCR), a more rapid analytical method for detecting and quantifying the presence of specific deoxyribonucleic acid (DNA) sequences—in this case, DNA sequences contained in FIB—is being evaluated. FIB and associated methods are being linked to health effects in beach users through a series of epidemiology studies. The *rapid* method has been defined variously as one that provides analytical results in 4–6 hours, which does not include transportation time to the laboratory, or laboratory preparation time. While laboratory methods are improving, results still might not be available on the same day samples are collected.

In 1999 before the BEACH Act of 2000 was enacted and EPA's grant-based monitoring and notification program began at coastal and Great Lakes beaches, EPA published a report, *Review of Potential Modeling Tools and Approaches to Support the BEACH Program* (USEPA 1999b). That report concentrates on rain threshold levels and the potential use of deterministic mixing zone, fate and transport, and hydrodynamic models and only briefly mentions statistically based models. This report includes statistical models, which have greatly increased in use since 1999.

Even with the advent of rapid methods, *real-time* or even *same-day* water quality data collected to inform the public of the risks of using a waterbody will not always be available. One means to supplement analytical results is to use statistical models and other predictive tools (such as rainfall threshold levels and notification protocols). Significant development and implementation of statistically based models has occurred, especially in the Great Lakes (Lake Erie and Lake Michigan) (Francy 2009; Nevers and Whitman 2005). All those predictive tools have proven to be reliable and cost-effective. EPA believes such predictive tools could be applicable in many other settings as well, including marine and inland beaches. Those tools develop statistical relationships or models between FIB densities (dependent variables) and various observations that describe the environmental conditions at the beach (independent variables). The models use recent and historical FIB densities and independent variables that include other water quality, hydrodynamic, and meteorological data to predict current levels of FIB and to forecast near-future levels of FIB or the likelihood of exceeding a water quality standard. Statistical models and other predictive tools can be run as frequently as data are available for measured independent variables and as long as models are shown to be producing reliable predictions that protect public health.

Rainfall-based notifications and closures have been widely used at marine and freshwater beaches for decades. Rainfall threshold levels are issued at some beaches on the basis of an analysis of historical data. At such beaches, it has been shown that after a certain amount of rainfall, a beach is likely to have high FIB densities (USEPA 1999). Other similar notification protocols could be developed in which a certain combination of conditions has been shown to result in high levels of FIB. For purposes of this document, rainfall threshold levels and other notification protocols are not considered as *models*, but as *predictive tools*.

2 Tools for Beach Notification Decisions

Statistically based models are being used to estimate water quality at many beaches in the United States, especially at beaches on the Great Lakes (Francy 2009). Rainfall threshold levels and other notification protocols are being used throughout the country. The primary reason for developing a predictive tool for beach notifications is to improve timeliness and accuracy of notification decisions and public notification in comparison to the current practice of waiting 18–48 hours for sample results before making a decision (Francy et al. 2006). Predictive tools might also be useful in developing or adapting routine monitoring programs to focus efforts when conditions favoring high FIB levels exist. The predictive tools examined in this report include statistical models, rain threshold levels, notification protocols, and deterministic models.

2.1 Statistical Models

A statistical model (also called a statistically based model or a *predictive model*) is a general term for any type of statistical modeling approach to predicting beach water quality. Linear regression models assume a linear relationship between factors, or combinations of factors, and FIB (Boehm et al. 2007; USEPA 2007; Nevers and Whitman 2005; Olyphant and Whitman 2004). The most highly developed statistical model approach is a multivariable linear regression relationship between FIB and several independent variables. Typical, easy-to-measure environmental and water-quality variables include the following: meteorological conditions (solar radiation, air temperature, precipitation, wind speed and direction, dew point); water quality (turbidity, pH, conductivity/salinity, UV/visible spectra); hydrodynamic conditions (flows of nearby tributaries, magnitude and direction of water currents, wave height, tidal stage); and other factors such as presence/number of birds or bathers. The most common model outputs are estimated levels of FIB or probability of exceedance of the state water quality standard for FIB. The process of developing a statistical model for beach advisories is explained in more detail in Chapter 5.

Statistical models are especially useful at some beaches and less useful at others. According to Francy (2006), statistically based modeling can also effectively predict water quality in situations where nonpoint or unidentified sources dominate, as well as in settings where discrete sources have been identified (Nevers and Whitman 2005). If a beach rarely has high bacteria densities or, conversely, almost always exceeds a bacterial water quality standard, it is unlikely that a statistical predictive model would significantly improve practices for timely decision making and notification. If a beach occasionally exceeds the water quality standard or if bacteria levels are frequently near the water quality standard level, statistical models can help by providing a timely prediction of whether FIB are likely to exceed the water quality standard according to parameters that are easier and faster to measure than FIB densities.

Modeling tools are used to supplement, not replace, monitoring, and their primary purpose is to make predictions because of the lag time between sampling and obtaining microbial indicator results. Developing and using a statistical predictive model is a dynamic process based on data collected via existing beach-monitoring programs. Statistical modeling employs a retrospective correlation of measured water quality (FIB levels) with conditions observed at the time of sample collection to produce an estimate of water quality that is time-relevant for recreational water management and use by the public. Model developers can create Internet-based systems that provide model predictions (similar to weather forecasts) to the public for the current period, not for a day or two in the past once exposure has already occurred. However, models need to be periodically validated and refined to improve predictions and better protect public health. More information on that topic is provided in Volume II of this report.

2.2 Rain Threshold Levels

When significant rainfall occurs in a short period, runoff is generally produced, which can carry harmful pollutants. Stormwater runoff and other surface water runoff (streams and rivers) are widespread primary pathways by which FIB and pathogens reach beaches (Lipp et al. 2001; Boehm et al. 2002; Schiff et al. 2003; Ackerman and Weisberg 2003). Runoff can contain animal feces and other bacterial sources that were deposited on land between storm events (Ackerman and Weisberg 2003). Runoff can also carry human sewage from leaks in the sewage transmission infrastructure (Ackerman and Weisberg 2003). Stormwater volume and pollutant loads generated depend on the characteristics of the drainage area, conditions of wastewater and stormwater infrastructure, and the volume and intensity of rainfall. The process of developing a rain threshold level, and other notification protocols, is explained in Chapter 6.

For some beaches, a defined intensity or duration of rainfall is frequently associated with observations of poor water quality. With that information, many beach managers and public health officials commonly issue a rain threshold notification after a rain event of a predefined intensity or duration. Beachgoers are familiar with routine, wet-weather closures in locations where they are implemented.

The objective of a rain threshold level is to identify a threshold level of rainfall at which FIB levels are likely to exceed the water quality standard. That is achieved if a statistical relationship between rainfall events and FIB densities can be observed or if a level of rainfall and rainfall conditions is consistently shown to be associated with increased FIB densities. The threshold can then serve as a management tool for developing notification protocols or predicting water quality standard exceedances requiring a beach notification. Several agencies have developed beach operating rules by studying site-specific relationships between rainfall and water quality monitoring data. Chapter 3 provides examples of such tools. Those types of tools are based on a simple regression or a frequency of exceedance analysis of simultaneous observations of FIB levels at representative monitoring stations near the beach and rainfall events at one or more locations at the beach or in the upstream watershed.

2.3 Notification Protocols

Notification protocols are based on a set of decision criteria and questions that trigger notifications in anticipation of poor water quality or other potentially hazardous conditions (rough waves, strong rip currents, red tide). This document focuses on only the water quality aspect of notification protocol. *Notification protocol* is a general term used to describe a protocol or a set of questions or decision points a beach manager routinely uses to determine whether to close a beach or issue a notification. The protocol can rely on sampling results, other information, or beach characteristics either alone or in addition to sampling results. A decision tree can be used as a type of notification protocol. Several states (see Section 4.3) use a series of questions or decision trees to guide their decisions for beach notifications. Such evaluations are designed to supplement bacteria data with characteristics of the beach that can influence the related bacteria levels (i.e., proximity to pollution sources, stormwater runoff, and current or wind direction).

Decision Trees and Binary Models

A decision tree classifies data from general to specific. It can be a simple tree that beach managers use to assess recent sampling results with other current conditions (such as rainfall amount and information on sewage bypasses) to decide whether to issue an advisory notification or to close a beach, and if so, for how long. If FIB are influenced by only one or two binary factors, a decision tree can be a simple and accurate predictive tool.

If the underlying correlation in a statistical model is being driven by critical environmental factors that change daily, the empirical relationship will always be somewhat unclear. The strength of statistical regression models is also their weakness. Regression analysis requires sufficient data to both establish the relationship between the predictive variables and observed water quality and define the confidence that can be placed in model predictions. The weakness of the prediction is that it is based on data, some of which cements the correlation, and some of which interferes with it. It is difficult to identify a particular set of circumstances that applies on a given day unless beach managers are fully aware of the relationship between FIB sources and their beach, and apply a discriminator to the observed data that incorporates that understanding.

An example of that would be a situation in which a stream outlet (a major source of FIB) was west of beach with an east-west oriented shoreline. A stiff breeze from either the west or east creates choppy water that causes turbidity to increase. Historic data indicate that turbidity is a fairly strong predictor of elevated FIB densities. When the wind is from the west, turbidity is high and FIB are being transported from the stream outlet to the beach. When the wind is from the east, turbidity is just as high, but the stream is no longer a source. Without wind information and knowledge of the stream source, a model prediction derived from only increased turbidity does not accurately inform the beach manager concerning the presence of pollution at the beach.

A decision tree modeling approach can handle such a situation as a set of decision points or yes/no junctions: IF turbidity is elevated AND the wind is from the west, THEN indicator densities will likely be elevated. Those decisions would likely be combined with other decision points stemming from a statistical analysis of historic beach data. Using the same scenario described above, a binary regression model would propose two different empirical relationships, one used when wind comes from the west and one for wind from the east.

Another binary model might use different sets of independent variables for early- and late-season observations, e.g., Ohio Nowcast (Francy and Darner 2007). Such an approach acknowledges that some variables might be more relevant in the early part of a season, but it might not be useful for prediction later in the season. The model developer analyzes both early and late season data, over a number of years. If the data set had not been segregated, its predictive power would be reduced by dilution because of changing circumstances. That approach is closely aligned to Hierarchical Bayesian Modeling, which has become more popular in the past decade.

An example of using a single, readily measured parameter is the use of turbidity. A strong correlation between turbidity and elevated FIB densities makes turbidity a strong predictive variable in a regression model. However, that univariate simplicity would not be desired in the situation where wind is the primary transport mechanism from the source to the beach or in the case where rainfall-driven turbidity is important but wind and wave-induced turbidity is irrelevant.

An interesting approach to decision tree modeling of bacterial indicator prediction is described in Bae et al. (2010). The commercial classification and regression tree (CART) software they used can perform tradition linear regression, but it can also classify data using a decision node approach. Each node is based on a response threshold with the strongest decision nodes occurring higher in the decision tree with less significant thresholds/variables having a lower place in the decision hierarchy. Each tree node is univariate in nature—a decision is made using a single independent variable. It allows for greater flexibility in defining the influence of different variables. Contrast that with multilinear regression, whose regression equation demands the participation of all independent variables in the model.

The goal of a classification tree approach is to minimize classification errors (i.e., false positives and false negatives). The CART method is more commonly used to address the question of whether a water quality standard will be exceeded than to produce a quantitative prediction of FIB. A successful CART model was designed for several beaches in South Carolina (Johnson 2007).

2.4 Deterministic Models

Deterministic models use mathematical representations of the processes that affect bacteria densities to predict exceedances of water quality standards. They include a range of simple to complex modeling techniques.

The 1999 EPA report *Review of Potential Modeling Tools and Approaches to Support the BEACH Program* (USEPA 1999b), mentioned in Chapter 1, includes various types of deterministic models such as mixing zone, fate and transport, and hydrodynamic models, as well as simple, predictive tools such as rainfall-curve-based closures. Specific deterministic models discussed in the 1999 report include CORMIX, EFDC (Environmental Fluid Dynamics Code), HSPF (Hydrological Simulation Program—Fortran), PLUMES, QUAL2E, Regional Bypass Model, SMTM (Simple Mixing and Transport Model), STORM, SWMM (Storm Water Management Model), and TPM (Tidal Prism Model). Those models were developed for general purposes, but they were perceived to have potential use in support of implementing criteria for beach notification and advisories. With the exception of the Regional Bypass Model, EPA is unaware of any widespread use for any of those models for predicting water quality at beaches. Most of the models used for timely beach notifications are statistically based models.

EPA believes there is potential for applying deterministic models to support the Beach monitoring and notification program. Using statistical models in combination with existing deterministic models, or *stacking* models, has been shown to have potential for increasing the quality of the results produced by using statistical models alone. That and other potential applications of deterministic or process models are described in detail in Chapter 8.

3 Hydrologic Environments and Their Effects on Modeling for Beach Notifications

3.1 INTRODUCTION

FIB are used to indicate the presence and extent of fecal pollution. FIB originate and thrive in the intestinal tracts of warm-blooded animals. Identifying sources of fecal pollution, tracking their movement through a watershed, and quantifying attenuation during transport within the aquatic environment are very difficult tasks, especially in highly dynamic shoreline environments. Having a good understanding of pollution sources and hydrologic setting can greatly improve model prediction accuracy, especially if that knowledge can be used to direct data collection efforts.

Fecal pollution sources can be roughly categorized into human sewage and animal sources (Schueler 1999). Human sources include publicly owned treatment works (POTW) discharge, runoff or seepage from septic systems, leaking wastewater infrastructure, and direct effects from bather shedding at the beach (Figure 3-1). The nature of the sources of FIB detected at a beach is of primary concern to beach managers and is part of the information that should be documented at beaches through the use of sanitary surveys (for more information on sanitary surveys, see Section 5.3.1.3).

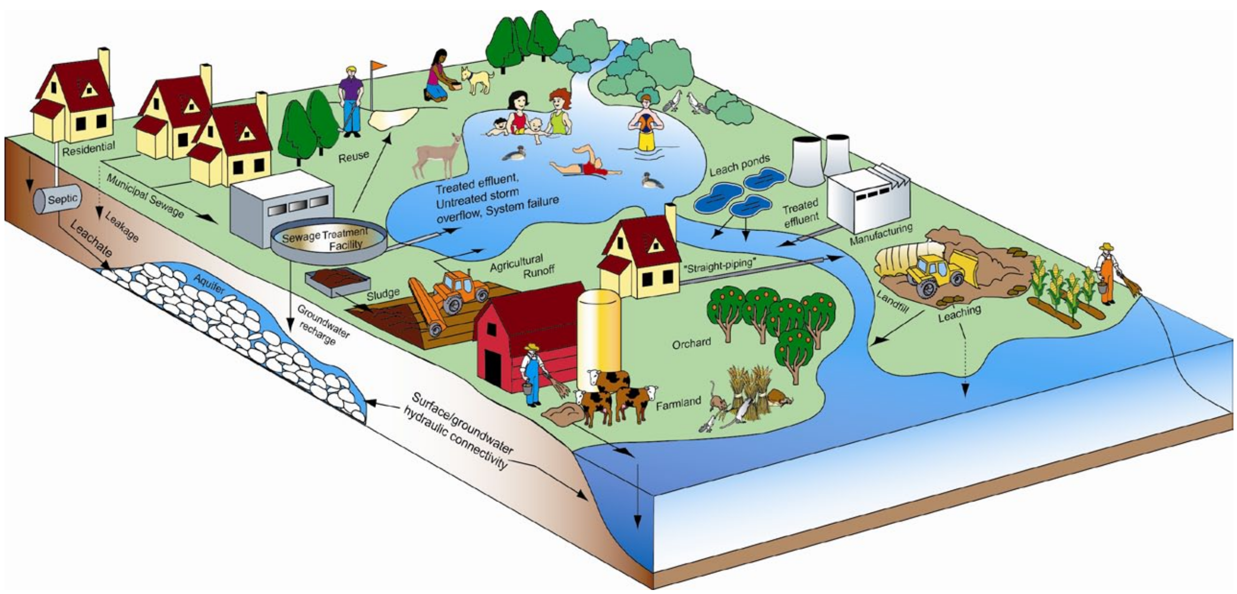

Figure 3-1. Sources and fate of fecal pollution in watersheds.

3.2 SOURCES OF FECAL POLLUTION IN THE WATERSHED

3.2.1 Animal Sources

Animal sources can be categorized as domestic animal sources and wildlife. Domestic animal sources consist of agricultural animals and pets. Wildlife includes birds, rodents, upland game animals, and marine animals, among others.

3.2.2 Human Sewage

The potential sources of human sewage vary depending on whether the watershed is sewered. In sewered watersheds, sources can be treated sewage, combined sewer overflows (CSOs), sanitary sewer overflows (SSOs), leaky wastewater infrastructure, illegal connections, and dumping to storm drains. CSO and SSO discharges are generally associated with storm events that cause capacity exceedances resulting in raw sewage (CSO) or partially treated sewage (SSO) flowing into natural waters. Power failures at pumping stations and line blockages and breaks also can result in human sewage reaching receiving waters. Illegal or improper connections to the sewer system and illegal dumping in storm drains are problems in some communities. Knowledge of outfall locations and the quantity and quality of storm sewer discharges is important for beach managers and should be determined by using a sanitary survey.

In non-sewered watersheds, human sewage is usually processed by septic systems or community package plants. If any part of the systems fails, human waste can escape and migrate to waterways. The design life of most septic systems is limited, usually in the range of 15 to 30 years, and proper maintenance of septic systems is widely variable. In watersheds with older systems and in heavily developed shore areas near lakes, faulty septic systems can be an important source of untreated human sewage.

By having some knowledge of what sources of fecal pollution are and where they are, data collection for predictive tool development can be focused on streams (for example) that are considered to be likely inputs of fecal matter.

3.3 BACTERIA MOVEMENT TO THE WATERBODY

Although the location and extent of pollution sources vary by the land use and ground cover in a watershed, a common characteristic is that loading to the receiving waterbody is usually strongly linked with the duration and intensity of storms. That is generally true for sewered areas and developed areas with failing septic systems.

In less developed watersheds, the bacteria in runoff take longer routes in reaching receiving waters, such as by detention and infiltration of stormwater in wetlands or in the soil. Such an environment reduces the direct flow of fecal pollution to waterways. Some areas have been developed to include infiltration ponds where stormwater is routed to the ponds where it infiltrates slowly, mimicking a natural system.

3.4 BACTERIA MOVEMENT WITHIN THE WATERBODY

Once in a waterbody, the chances that fecal pollution and associated FIB move into swimming areas depend on many variables including the distance of the point of entry from the swimming area, effluent mixing and transport by currents, sediment settling and resuspension, and fate and transport factors experienced by the bacteria that affect survival. Those processes and factors differ greatly according to the receiving waterbody. Lotic (flowing water) environments such as rivers and streams present conditions very different from lentic (still water) environments such as lakes. Oceans and estuaries are influenced by tides (affecting bacteria movement), longshore currents, waves, and saltwater (affecting survivability). Geography, climate, rainfall, drainage, and other conditions also play important roles in determining the final occurrence of fecal pollution in a waterbody.

3.5 HYDRODYNAMIC FACTORS AFFECTING POLLUTION MOVEMENT

3.5.1 Hydrodynamic Dispersal in Lakes and Other Lentic Environments

When an effluent stream enters a standing body of water, the incoming water flows into the density layer in the receiving waterbody that is most similar to its density. Density is governed primarily by temperature and dissolved and suspended material.

Three types of inflow water movements can result, depending on density differences between the inflowing water and the receiving water:

1. *Overflow*—inflow water density is less than the receiving water density
2. *Underflow*—inflow water density is greater than the receiving water density
3. *Interflow*—inflow water enters the receiving water at an intermediate depth

The extent of turbulent mixing that occurs depends on the volume and velocity of the influx. Once in the open water, the inflow velocity is reduced, and the mixing zone expands. The reduction of flow velocity typically enhances deposition of suspended material.

Unlike lotic environments where water movement in the waterbody is generated primarily by downstream flow, the directional movement of bacteria in lentic environments is generated primarily by the transfer of wind energy to the water. The frictional movement of wind blowing over water sets the water surface into motion, producing traveling surface waves. In deep water where wave length is much less than water depth, that motion is confined to surface layers with little effect on the displacement of deep waters. In shallower waters, when wavelength becomes more than 20 times the water depth, the wave becomes a shallow water wave, and the cycloid motions are transformed into a to-and-fro sloshing that can extend to the bottom of the water column. Morphometry of the water basin, stratification structure (density layers), and the area exposed to wind all contribute to water turbulence, currents, and mixing and transport of bacteria cells into and out of a swimming area.

Settling and resuspension of bacteria are important factors in lentic environments because of wind-generated water turbulence. Unlike streams, which transport resuspended sediments downstream, nearshore sediments tend to stay nearshore except in the case of powerful storms. Because bacteria cells tend to survive longer in sediment than in open water (Sherer et al. 1992; Burton et al. 1987; Thomann and Mueller 1987), the resuspension factor can make sediment an important source of bacteria in swimming areas.

3.5.2 Hydrodynamic Dispersal in Streams and Rivers

Streams and rivers are lotic environments. Bacteria-laden effluent entering such environments moves and disperses in the direction of the flow. In idealized conditions of constant width, depth, area, and velocity, the stream will have uniform flow. That condition rarely occurs in natural channels, however (FISRWG 1998). Uniform flow is typically disrupted by meander bends, changes in cross-section geometry, and channel features and obstructions such as fallen timber, boulders, sand bars, riffles, and pools, which cause turbulence, mixing, and the convergence, divergence, acceleration, or deceleration of flow. Those conditions, combined with flow volume and velocity and the influence of survival factors, such as water clarity, affect the appearance of bacteria in a lotic swimming area.

The nature of a waterbody strongly influences the ability of statistically based regression models to effectively predict FIB densities in waters adjacent to swimming beaches. In the following paragraphs, the amenability of Great Lakes locations, inland lakes, rivers, and marine settings are discussed relative to the modeling process.

3.6 Great Lakes Hydrologic Environment

The five Great Lakes represent a distinctive hydrologic environment in North America. They are the largest freshwater bodies on the continent. The Great Lakes, with the exception of Lake Erie, all have maximum depths greater than 200 meters. The Great Lakes experience very little tidal effect but, nevertheless, do experience variations in water level due to wind and season. Like the oceans, they can be greatly disturbed by storms. Unlike marine settings, the Great Lakes represent a relatively confined set of environments and are separated from the global currents that characterize the oceans. Discharges to the Great Lakes, therefore, are more likely to have a local cumulative effect.

The hydrologic environment of the Great Lakes has been modeled extensively (Schwab and Bedford 1994; Nevers and Whitman 2005) and, as detailed later in Chapter 4, has been the focus of most of the successful statistical predictive modeling efforts of FIB at swimming beaches. That comparative success stems in part from the fact that turbulent mixing, and thus FIB variability, is more dynamic at marine beaches that are strongly affected by tides, surge, and wave action. In addition, the lower number of variables associated with Great Lakes hydrologic environments has facilitated the implementation of deterministic hydrodynamic and fate and transport models as described in Chapter 7.

3.7 Inland Lakes

Inland lakes constitute waters that are amenable to statistical modeling and to using other predictive tools such as rainfall threshold levels. Smaller inland lakes are less likely to be receiving waters for POTWs but can become more degraded from overdevelopment and high levels of recreational use. Desirable lake locations can be affected by septic systems and can be very sensitive to runoff effects if little water exchange occurs through the lake system. Inland lakes are also sensitive to effects from nitrogen and phosphorous pollution, which can increase water column turbidity, thereby reducing the effects of degradation by sunlight (insolation) on FIB and pathogens.

3.8 Rivers

Statistical models for predicting FIB densities for the likelihood of exceedances have been successful in at least three rivers, as described in Chapter 4. Rivers lend themselves to statistical modeling. They possess a predictable flow direction and easily gauged water level and flow velocity. In addition, the locations of permitted discharges are known, and travel times from other features, such as tributaries, are readily determined. Accordingly, rivers tend to respond predictably to varying conditions and yield good modeling results.

Because of the good understanding of fluvial processes and well-studied mixing and transport characteristics, rivers can be also good systems for developing and using deterministic models. Deterministic models in rivers have been used in National Pollutant Discharge Elimination System permitting and for other in-stream water quality assessment purposes relating to Clean Water Act programs. Some examples of those models are the EPA Hydrological Simulation Program—FORTRAN (HSPF) (www.epa.gov/ceampubl/swater/hspf) and the EPA Stormwater Management Model (SWMM) (www.epa.gov/ednnrmrl/models/swmm/index.htm). However, they are not used for beach notifications.

3.9 Marine Waters

Marine waters constitute the most challenging environment for statistical predictive models because of the complex hydrodynamic nature of ocean settings and the resulting high number of variables associated with them. The effects of large tidal ranges ($\geq$9 feet) and resulting tidal currents and changes in flow direction have, in the past, made marine models more the focus of deterministic modeling efforts (Zhu 2009). Some state beach programs (e.g., South Carolina and Maine) are implementing statistically based models. Within the range of ocean beaches, a wide variety of site characteristics exists, some of which will be more amenable to use in statistical models than others. Beaches in estuaries, harbors, and coastal embayments are less dynamic than beaches on the open ocean and, thus, might be good candidates for statistical modeling. As with freshwater settings, not all swimming beaches can benefit from the use of statistical predictive models. For many settings, however, statistically based models will be effective, and those settings will become apparent as beach managers experiment in coming years.

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4 Current Applications of Predictive Tools

Various predictive tools (statistical models, rainfall thresholds, and notification protocols) are being used as part of beach management programs across the United States. EPA reviewed the tools that are in use or almost complete, and this chapter includes a short description of each for which information was available. Table 4-1 provides an overview of the predictive tools. EPA has successfully used Virtual Beach at several freshwater and marine sites. They are described in Volume II of this report.

Table 4-1. Overview of predictive tools in use

Location	Prediction method	Areas of application
California	Rain threshold level	Southern California counties
Connecticut	Rain threshold level	Cities of Greenwich, Norwalk, and Stamford
Delaware	Rain threshold level	Entire state
Florida	Rain threshold level	Individual cities
Hawaii	Rain threshold level	Entire state
Georgia	Statistical model	Chattahoochee River
Illinois	Statistical model	Great Lakes beaches
Indiana	Statistical model	Great Lakes beaches
Kansas	Statistical model	Selected rivers
Maine	Notification protocol	Entire state
Maryland	Statistical model and notification protocol	Sandy Point State Park (in development)
Massachusetts	Statistical model	Charles River
New Jersey	Rain threshold level	Six beaches
New York	Regional hydrologic model combined with local notification protocol	New York City
Ohio	Statistical model	Great Lakes beaches
Pennsylvania	Statistical model	Schuylkill River
Rhode Island	Notification protocol	Entire state
Scotland	Rain threshold level	Various beaches
South Carolina	Statistical model and notification protocol	Georgetown and Horry counties
Washington	Notification protocol	All counties
Wisconsin	Statistical model	Ozaukee County

Note: The information provided in this chapter is based on personal communications with state contacts and other responsible agency personnel. In some instances, references of published works are available. Those references are listed in Chapter 9. The topics discussed with beach contacts are summarized in Appendix A. EPA realizes that new models are continually being developed. Table 4-1 is not an exhaustive list of all the tools being used or developed for beach management. EPA welcomes input on additional predictive tools in use or being developed for beach programs.

4.1 STATISTICAL MODELS

Statistical models are created on the basis of observed relationships among variables such as sunlight, temperature, turbidity, input flows, wind speed (and other variables that can affect bacteria loading or survival rate) and indicator bacteria levels. Such models have been found to be useful for making timely beach notification decisions. Model outputs can be estimated densities of indicator bacteria or probability of exceeding a threshold level such as the state water quality standard. That information is used in making a beach notification decision. The models are described in more detail in Chapter 5. This chapter provides short descriptions of statistical models in use.

As shown, a number of statistical models are successfully implemented at Great Lakes beaches. Local and state agencies managing beaches on the Great Lakes have put an extraordinary effort into protecting the health of recreational users by working with the U.S. Geological Survey (USGS) and independently to pioneer the method of statistical modeling (and other predictive tools) for timely beach notifications. Much of the work has been published in the scientific literature by USGS and others. Table 4-2 summarizes the statistical models recently used or in development.

Table 4-2. Beaches assessed using predictive tools

Name	Beach	Model inputs	Model output	Leading agencies	Status
SwimCast	Beaches (four) in Lake County, Illinois	Air temperature Wind speed Wind direction Precipitation Relative humidity Lake stage Water temperature Water clarity Insolation Wave heights	Estimated *Escherichia coli* concentration	Lake County Health Department, Lakes Management Unit	In use
SwimCast	63rd Street Beach, Chicago Park District, Illinois	Flow Rainfall Sunlight Temperature Turbidity Wave height Wind speed	Estimated *E. coli* concentration	Chicago Park District (with Remote Data, Inc.)	Applied for trial period
Nowcast	Lake Erie Beaches, Ohio	Day of year Lake level Rainfall Temperature Turbidity Wave height	Probability that water quality standard will be exceeded	U.S. Geological Survey	In use

Name	Beach	Model inputs	Model output	Leading agencies	Status
Nowcast	Upper Lake Park, Ozaukee County, Wisconsin	Day of year Lake level Rainfall Temperature Turbidity Wave height	Probability that water quality standard will be exceeded	U.S. Geological Survey	In use
Project S.A.F.E.	Lake Michigan Beaches, Indiana	Gauge height Rainfall Chlorophyll a Turbidity Wind direction	Probability that water quality standard will be exceeded	Indiana Department of Environmental Management	In use previously and currently under revision
RainFlow	Upper Lake Park, Ozaukee County, Wisconsin	24-hour rainfall 48-hour rainfall Bacteria composite sample Lake conditions Turbidity Stream flow Stream velocity	Yes/No advisory based on water quality standard	Ozaukee County	Used before switching to Nowcast
South Shore Beach Model	South Shore Beach, Milwaukee, Wisconsin	Algae Chlorophyll *a* Conductivity *E. coli* concentration from previous sample Temperature Wave direction Wave vector	Estimated *E. coli* concentration	City of Milwaukee	Under consideration
Flag Program	Charles River, Boston, Massachusetts	Rainfall Recent bacteria sample	Predicted concentration and probability of exceeding secondary standards	Charles River Watershed Association	In use
PhillyRiver-Cast	Schuylkill River, Philadelphia, Pennsylvania	Flow Rainfall Turbidity	Yes/No advisory based on water quality standard	Philadelphia Water Department	In use
BacteriAlert	Chattahoochee River near Atlanta, Georgia	Flow Turbidity	Low/High risk level	U.S. Geological Survey	In use
Stormwater Model	Horry County, South Carolina	Cumulative rainfall Current UV level Current weather Moon phase Preceding dry days Rainfall intensity	Estimated *E. coli* concentration	Horry County (with the University of South Carolina)	In use and being recalibrated
Stormwater Model	Fairhaven Beach, Lake Ontario, New York	Rainfall Turbidity Current speed Current direction	To be determined	USGS and New York State	Being developed

Name	Beach	Model inputs	Model output	Leading agencies	Status
Stormwater Model	Sandy Point State Park, Chesapeake Bay, Maryland	Day Moon phase Rainfall Salinity Temperature Wind speed	Yes/No advisory based on water quality standard	National Oceanic and Atmospheric Administration & University of Maryland	Being developed
Receiver Operating Characteristic Curve Analysis for Boston Harbor Beaches	Constitution Beach in East Boston, Carson Beach in South Boston, Tenean Beach in Dorchester, and Wollaston Beach in Quincy	Antecedent rainfall	Yes/No advisory based on water quality standard	Massachusetts Department of Conservation and Recreation and Massachusetts Water Resources Authority	In use
Unnamed	Little Arkansas River, Rattlesnake Creek, and Kansas River, Kansas	Seasonality Turbidity Temperature Chlorophyll Dissolved oxygen Other water quality parameters	Estimated fecal coliform and nutrient concentrations	U.S. Geological Survey	Not in use

4.1.1 SwimCast (Lake Michigan Beaches, Illinois)

Several Lake Michigan beaches are using a program called SwimCast to predict *Escherichia coli* (*E. coli*) densities. In Lake County, Illinois, the program is installed at several beaches, including Forest Park-Lake Forest, Rosewood-Highland Park, and Waukegan Beach. Meteorological equipment is on a station in the lake to measure air temperature, wind speed and direction, precipitation, relative humidity, lake stage, water temperature and clarity, insolation (sunlight), and wave height. The data are transferred to a data logger and used in an equation to predict the *E. coli* density. Sampling is still performed at the beaches 4 days a week between May and September, and, as a result, predictions have been approximately 90 percent accurate. Lake County has been using the SwimCast system since 2004 and provides daily data and beach notifications on its website.

Chicago Park District is also testing the SwimCast program. It announced SwimCast for a trial period at the 63rd beach in 2008, and the District plans to apply the model once it is calibrated efficiently enough to provide 90 percent accuracy. Additional information on SwimCast's use in Lake County, Illinois, is at www.lakecountyil.gov/Health/want/SwimCast.htm.

4.1.2 Nowcast (Lake Erie Beaches, Ohio)

The Ohio Nowcast provides advisory information based on predictive models for two Lake Erie beaches (Huntington and Edgewater) and one recreational river site (Cuyahoga River at Jaite). The models are uniquely fitted to the characteristics of each beach using multivariable linear regression (further explanation is in Chapter 5). Water samples are collected daily and analyzed for indicator microbes and other parameters to obtain inputs for the model. The inputs are turbidity, rainfall, wave height, water temperature, day of the year, and lake level. The model produces a probability of exceeding the 235 colony forming units (CFU) per 100 milliliters (mL) standard for *E. coli*. The *probability threshold* is site-specific, based on historical data, and is set by the beach manager for decision making. For example, a beach manager might decide post an advisory if there is a 25 percent probability of exceeding the water quality standard. During model development, water quality sampling continued so that decision accuracy could be tested. The number of *false positive* and *false negative* predictions were calculated. The probability threshold is reconsidered for maximizing correct decisions (Francy 2006). The use of models at other Lake Erie beaches has been investigated, and the beach models are all in different phases. Development of models for Villa Angela and Lakeshore were suspended because the model results were not more accurate than the use of the persistence model. At Maumee Bay State Park, a model was developed with variables for turbidity and wind direction; it was validated during 2010 and is available to include in the Ohio Nowcast in 2011. During 2010, data were collected for model testing at Lakefront Park (Huron, Ohio), Mentor Headlands State Park, and Fairport Harbor Lakefront Park. Further information is available at: http://www.ohionowcast.info/nowcast_technical.asp.

4.1.3 Nowcast (Port Washington, Wisconsin)

In 2009 Ozaukee County Public Health Department partnered with the Wisconsin Department of Natural Resources to develop an operational Nowcast model at Upper Lake Park Beach in Port Washington, using Virtual Beach software to develop the model. It took approximately 40 hours of combined staff time to develop it, using data collected during the 2007 and 2008 beach seasons through routine beach monitoring and data collection. Variables used in the model are wave height, turbidity, 24- and 48-hour rainfall, stream flow, water and air temperature, and the previous day's lab results on *E. coli* (when they are available). The model is used to predict *E. coli* densities four days a week. Running the model takes approximately 5 minutes per day as part of routine monitoring activities. County staff enter daily data for each of the explanatory variables into the model and report the results (swimming advisory or not) on the Wisconsin Beach Health website (www.wibeaches.us).

The model proves to be highly accurate, with a mean absolute error of 15 CFU/100 mL and an overall R^2 of 62 percent. A visual inspection of the model's performance confirms that the model was highly sensitive to small fluctuations in *E. coli* concentration during 2009.

4.1.4 Project S.A.F.E. (Indiana)

Project S.A.F.E. (Swimming Advisory Forecast Estimate) is a statistical predictive model applied to four beaches in Indiana (Lake Street, Marquette Park, Wells Street Beaches of Gary, and Ogden Dunes in Portage Township). The model is specifically designed to include the pollutant load coming from a significant outfall near the beaches (Burns Ditch). The model uses characteristics of the individual beaches, wind direction, rainfall, chlorophyll *a*, turbidity, and Burns Ditch gauge height. The model is run daily to obtain the predicted likelihood that the *E. coli* concentration will exceed safe limits. The beach managers can use the probability to determine if a beach should be closed or under advisory. USGS developed the Project S.A.F.E. model (Whitman 2008).

The model is being applied in combination with a regional Hydrodynamic Model for Lake Michigan, which the National Oceanic and Atmospheric Administration (NOAA) developed. The NOAA model simulates to a high degree of accuracy frequent changes in direction of long-shore current in this region of Lake Michigan. The data is combined with the Project S.A.F.E. statistical model for more accurate beach water quality predictions than the Project S.A.F.E. model alone.

Project S.A.F.E. has been under revision for several years and is expected to be put back in use soon. Additional information on Project S.A.F.E. is at www.glsc.usgs.gov/main.php?content=research_projectSAFE_about&title=Project%20S.A.F.E.0&menu=research_initiatives_projectSAFE.

4.1.5 RainFlow (Port Washington, Wisconsin)

Before using Nowcast at Upper Lake Park in Port Washington, Wisconsin, bacteria levels were estimated daily using a model named RainFlow (City of Port Washington 2007). No stormwater controls are in Port Washington, and the nearest source of runoff affecting the beach is Valley Creek. The model used the velocity and volume of water passing through Valley Creek in combination with recent rainfall data and a turbidity reading at the beach to provide a notification recommendation. Valley Creek parameters and turbidity were taken by Ozaukee staff; daily rainfall was measured at the Port Washington Wastewater Treatment Plant (WWTP) just south of the beach. The overall model accuracy according to historical observations and predictions was 90 percent. The model was validated with daily composite samples. In the 2008 season, the model correctly recommended if advisory notification was needed 94 percent of the time. Upper Lake Park now uses Nowcast, as described earlier.

4.1.6 South Shore Beach Model (Milwaukee, Wisconsin)

In Milwaukee, the city attempted using models for Bradford Beach and South Shore Beach. The city aborted the Bradford Beach model because the maximum sensitivity that could be obtained for estimating the indicator concentration was only 80 percent. The city is considering the South Shore Beach Model. That model would require a weekly calibration and the *E. coli* concentration determined in the previous 24 hours. None of the nearby laboratories are open 7 days a week. The city is confronting other issues such as equipment costs, sensitivity, and available staff. However, EPA has successfully modeled South Shore Beach, and details about that effort are in Volume II of this report.

4.1.7 Charles River Flag Program, Massachusetts

The Charles River Watershed Association has been using the Flag Program since 1998 to estimate and communicate the potential risks associated with recreational activities in the river each day. The association samples bacteria approximately twice each week and uses the data in the model estimations along with current rainfall data. Model estimates are based on ordinary least squares and logistic regression models (explained further in Chapter 5). The model predictions are posted online for nine sites, and four sites along the river have a water quality flag to communicate to recreational users. Most of the river is designated for secondary contact recreation (boating), and a fecal coliform bacteria target is based on that use. Red flags are raised at the four monitored stations if the probability of the river exceeding boating standards is equal to or greater than 50 percent. If the probability is less than 50 percent, a blue flag is raised. Yellow flags are used when there is uncertainty of the water quality or other factors could be affecting boater safety (e.g., Cyanobacteria). Red flags are normally raised only after heavy rainfall.

For more information about and updates to the program, see www.crwa.org/water_quality/daily/daily.html.

4.1.8 PhillyRiverCast (Philadelphia, Pennsylvania)

The PhillyRiverCast is a Web-based water quality forecasting system developed by the Philadelphia Water Department to provide the public with information on the status of the Schuylkill River. The model uses real-time turbidity, flow, and rainfall data to predict fecal coliform concentration. It runs automatically and updates the ratings every hour on the basis of the estimated current fecal coliform concentration. The website also explains what recreational activities are considered safe for the estimated bacteria levels (Maimone et al. 2007). For more information and updates, see www.phillyrivercast.org/; for information about how the model was created, see www.phillyrivercast.org/Nav_howcreated.aspx.

4.1.9 BacteriALERT (Chattahoochee River, Georgia)

The Chattahoochee River BacteriALERT program monitors similarly to the PhillyRiverCast system, using real-time turbidity readings and flow. Unlike the PhillyRiverCast system, BacteriALERT does not use rainfall. Using the current flow as an input captures the influences of rain on bacteria levels and most regular operation of the upstream Buford Dam. The model also runs automatically and updates recreational users via a website every hour. The ultimate posting by BacteriALERT is a risk level for exposure to harmful bacteria and organisms (none, low, or high), as suggested from the estimated *E. coli* concentration. A low risk is an *E. coli* concentration of < 177 CFU/100 mL, and a high risk is posted if *E. coli* counts are estimated to be more than 235 CFU/100 mL.

The BacteriALERT program is a partnership between state and federal agencies and nongovernment organizations. It was first tested on the Chattahoochee River. Additional details on the entire Chattahoochee River project are at http://ga2.er.usgs.gov/bacteria/SummaryIntroduction.cfm.

4.1.10 USGS Model (Kansas)

The USGS used in-stream water quality monitoring results and regression equations to estimate real-time bacteria and nutrient concentrations for two stations in the Little Arkansas River and one station in the Kansas River and in Rattlesnake Creek. Stream gauges were installed at each location. The stations monitor turbidity, water temperature, specific conductance, dissolved oxygen (DO), pH, and total chlorophyll. The water quality data were used to develop a relationship between fecal coliform and the water quality parameters that could be measured in-stream. Each regression equation was specific to its stream. The purpose of the model was to calculate accurate loads for various parameters, not for public health advisories. Turbidity and seasonality were significant variables for the bacteria estimations at all locations. No information is available to confirm whether the model is applied. It is possible that the model is used at such a local scale that it is not well publicized. Christensen et al. (2001) describe their experience with the model.

4.1.11 Stormwater Model (Horry County, South Carolina)

A model used in South Carolina was developed with assistance from the Public Health Department of the University of South Carolina. The model is a combination of two separate methods, each of which estimates the bacteria concentration in the water each morning, mainly using cumulative rainfall, rain intensity, preceding dry days, current weather conditions, and tide information according to moon phase. One model uses a multivariable linear regression to predict an estimated bacteria concentration. The other model uses the CART method to estimate what range the bacteria concentration will be (high, medium, or low). The estimated bacteria concentration range and the estimated bacteria concentration are combined to approximate a third possible bacteria concentration, called the Ensemble prediction. The beach manger uses all three outputs to determine the necessary notification level.

The model series is applied to 10 beaches in Horry and Georgetown counties. The model self-extracts rainfall data from rain gauges at each beach and independently inputs weather and tidal information. Data are continuously added to the model, which is constantly recalibrated. A more intensive recalibration is underway to adjust to infrastructure changes. Recently, a stormwater outfall pipe was extended further into the ocean at one of the beaches. That is expected to significantly affect the model's calibration. The beaches have a standard and constant warning of health risks while swimming, meaning there is always some level of notification on the beaches.

4.1.12 Stormwater Model (Fairhaven Beach, New York)

New York also attempted modeling at Fairhaven Beach on Lake Ontario, motivated by exceedances in 2005 and 2006. The managers were considering statistical predictive models that would use rainfall, turbidity, and current speed and direction as dependant variables. Acoustic Doppler Current Profiler equipment would be used to measure the currents. The following 2 years did not have as many bacteria exceedances; therefore, there was less of a demand for the effort.

4.1.13 Stormwater Model (Sandy Point State Park, Maryland)

In the spring of 2006, Sandy Point State Park in Maryland received several days of heavy rainfall, which closed the beach for the first time in recent knowledge. Now, the managers of the park, which is on the Chesapeake Bay shoreline, are developing a model to regularly estimate the concentration of bacteria in the beach water. The model developers collaborated with South Carolina. Similar to the South Carolina models, multivariable linear regression, CART, and ensemble methods will be used to develop a trio of results.

Intensive sampling was performed in 2007 and 2008 but, unfortunately, the sampling protocol was recently changed, and sampling will need to be repeated using the new procedure. The earlier sampling and model development demonstrated strong effects on bacteria from temperature and salinity.

The model is expected to be complete in the next 2 to 3 years. The managers carefully chose the software (GIS and R) for the model so that the model could be used by other agencies for bacteria prediction. The managers intend for the model to be applied at other Chesapeake Bay beaches in the future.

4.1.14 Virtual Beach Manager Toolset (Various Locations)

Virtual Beach is a set of decision support software tools developed to help local beach managers make decisions as to when beaches should be closed because of predicted high levels of FIB. EPA’s lab in Athens, Georgia, is developing the tools in support of the BEACH Act. One primary function of Virtual Beach is a data exploration and model builder tool that facilitates developing a multivariable linear regression equation for predicting FIB densities for a beach on the basis of environmental data such as wave height and water temperature. Another function of Virtual Beach is to take a *best fit* multivariable linear regression model for a data set and automatically pull in (from Internet sources) distributed data for the significant independent variables of the model. The model user can also enter criteria for decision making that will maximize correct predictions. Virtual Beach should benefit the beach-going public by helping beach managers make more accurate and timely beach notification decisions. Virtual Beach’s testing and deployment was done with the collaboration of several Great Lakes states and organizations (Wolfe et al. 2008). Virtual Beach is thoroughly documented in Volume II, Chapter 1 of this report.

4.1.15 Receiver Operator Characteristic Curve Modeling in Boston Harbor Beaches (Boston, Massachusetts)

In 1996 the Massachusetts Department of Conservation and Recreation and Massachusetts Water Resources Authority began a study to intensively monitor a subset of beaches to better understand variability in water quality and to develop predictive tools to make timely beach decisions. Beach selection was in part based on the number and variety of urban pollution sources including storm drains, CSOs, illicit sewer connections, boats, and animals (e.g., birds, dogs). Four urban beaches were selected: Constitution Beach in East Boston, Carson Beach in South Boston, Tenean Beach in Dorchester, and Wollaston Beach in Quincy.

The Department of Conservation and Recreation and Massachusetts Water Resources Authority teamed up with a Harvard School of Public Health biostatistician to create multiple linear regression models. The models incorporate tide, rainfall, sunlight, temperature, days since last rain, wind strength, and direction. However the models were not able to explain 30 percent to 40 percent of variability in bacteria counts.

Subsequently, they used a prediction tool, Receiver Operating Characteristic (ROC) Curves, which were developed in the 1940s to make sense of radio signals used to analyze radar images during World War II. Beginning in the 1970s, they were recognized as useful for interpreting medical test results. ROC curves have the advantage of being simple to use: they compare the effectiveness of several swimming advisory triggers, including the previous day's *Enterococcus* levels and rainfall. However, the analysis requires daily monitoring for a prolonged period.

The ROC curve analysis will identify two water quality conditions: swimmable and not swimmable. ROC curve analysis evaluates the overall ability of an indicator variable to correctly *classify* beach water quality as suitable or unsuitable for swimming, and it allows direct comparison of different indicator variables by a common metric. It facilitates the identification of a maximum threshold value for the indicator variable that produces a desired true positive rate and false positive rate.

In the Boston Harbor analysis, the researchers concluded that the previous day's *Enterococcus* levels are an inadequate indicator for determining beach use daily at every beach; antecedent rainfall is usually a more accurate indicator and is available in real-time (Morrison et al. 2003).

4.2 Other Predictive Tools

4.2.1 Rain Threshold Levels

For many beaches, intensity of rainfall correlates to observations of poor water quality. Agencies use historical data to identify the relationship between rainfall amount and bacteria levels and then apply a threshold of rainfall beyond which the beach will be under advisement. How rainfall thresholds are determined differs among states and localities.

Stormwater runoff is a primary pathway by which bacteria loads reach waterbodies and beaches. The amount of stormwater generated depends on the characteristics of the drainage area and the amount and intensity of rainfall. When significant rainfall occurs in a short period, more runoff is produced, which can carry harmful pollutants in its course.

Many beach managers can directly relate the concentration of bacteria to the amount of rain received in nearby areas. Using historical data, the localities are able to observe a relationship between rainfall and resulting bacteria densities. Managers can then use that relationship to identify an intensity of rainfall (or threshold) that is likely to cause exceedances of water quality standards and the length of time in which the standards will be exceeded.

Table 4-3 shows the places that use rainfall measures to directly predict the need for recreational waters notifications. Each broader jurisdiction or local beach can apply the determined rainfall threshold differently. The sections below discuss how managers are using rain thresholds to trigger advisories in anticipation of poor water quality.

Table 4-3. Beaches assessed using rainfall thresholds

Location	Rainfall threshold	Notification period	Notification	Area covered by threshold
California	0.25 centimeters (cm)	3 days	General advisory	Los Angeles County beaches
California	0.5 cm	3 days	General advisory	Orange County beaches
California	0.5 cm in 24 hours	3 days	General advisory	San Diego County beaches
Delaware	7.5 cm in 24 hours	Until clean sample	No-swimming advisory	All beaches
Hawaii	Flash flood warning	3 days	Brown water warning	Whole island or state[a]
New Jersey	2.5 cm in 24 hours 7.1 cm in 24 hours	24 hours 48 hours	Closed	Six beaches
New York City, New York	0.5 cm in 6 hours 1.0 cm in 24 hours (beach dependent)	24–48 hours (beach dependent)	Yellow advisory level	All city beaches
Milwaukee, Wisconsin	2.5 cm in 24 hours	48 hours	Yellow or red advisory level	All (five beaches)
Scotland	Beach specific	Beach specific	No-swimming advisory	Individual beach

a. Island-wide or state-wide, depending on weather patterns

California

Several counties in California preemptively issue recreational notification at their beaches using a rainfall threshold. Little rain falls through most of the year in Southern California. Consequently, even a light storm can produce runoff with concentrated amounts of pollutants. The rainfall thresholds are set much lower than the rest of the country—normally in the range of tenths of an inch. Most counties post beach advisories for 72 hours after the rain threshold has been met.

Connecticut

Using compiled bacterial analyses to predict water quality when certain conditions are observed provides a way to establish a proactive public health policy. In a study by Kuntz and Murray (2009) the authors reviewed the use of the geometric mean of various conditions including the amount of rain in previous days, wind direction and speed, tides and high tide height, water temperature, and drought or flood conditions for the season, different materials coming into the swimming areas, and the location and amount of any sewage spills as possible predictors of water quality exceedances. Only three events showed statistical significance (Chi-squared $p < 0.0001$):

- Rain events of one inch or more in a 24-hour period under normal weather conditions
- Rain events of more than one-half inch in a 24-hour period under drought conditions
- When *floatable* material from distant sewage spills (i.e., grease balls) are present at a beach

Such evaluations enable a public health policy to be easily developed that restricts swimming when certain identified conditions are present without waiting for sampling results to prove that a problem exists.

Delaware

Delaware developed its rainfall threshold levels in 1993 through intensive local sampling at several locations and still uses the levels. Marine waters and coastal beaches are not affected by rainfall or stormwater as much as the inland lakes and bays; therefore, the rain threshold is relatively high compared to other states. The threshold level for Delaware marine waters and coastal beaches is 3 inches (in), and a notification lasts for 24 hours. The inland waters of Delaware have much lower rain thresholds. For the inland waters, closure length and rain threshold are individually determined by lake.

Hawaii

Unlike most states using a rainfall threshold, Hawaii does not have a specified rainfall intensity for which a notification is automatically issued. A *Brown Water Warning* is automatically posted if a flash flood warning is issued by the National Weather Service (NWS) and is posted for all beaches on the island for which the flash flood warning applies. In other times of heavy rain (or steady rain over several days), a Brown Water Warning might be posted depending on staff assessments of the weather and visual observations. For most Brown Water Warnings, a beach advisory is issued for 3 days after the posting. However, notifications can last from a few days to more than a week, depending on whether the rain continued, the amount of silt discharged, and the water currents.

New Jersey

New Jersey has six beaches that close automatically if a rain threshold is reached. Four of the beaches are affected by a pond outfall pipe, and the other two beaches are small, river beaches affected by stormwater runoff and a marina. Five of the six beaches close for 24 hours if it rains 2.5 cm (1 in) within a 24-hour period, and 48 hours if it rains 7.1 cm (2.8 in) within a 24-hour period. The thresholds of the four beaches affected by the pond outfall pipe are being reevaluated because the pond outfall pipe has been extended 300 feet into the ocean. The pipe extension could lessen the effect of the stormwater discharge and, consequently, raise the rain threshold. The two beaches affected by the small river input are not affected by the lengthening of the stormwater pipe.

Most beaches in New Jersey do not have a rainfall threshold level for notifications and rely on traditional sampling to determine levels of potential risk.

New York City, New York

In New York City's complex coastal hydrologic setting, which is affected by tides, river flow, stormwater, and sewage treatment outfalls, existing regional models have helped determine the times and locations where recreational water quality standard will be exceeded because of rainfall and associated stormwater and CSO bypasses. The New York City Department of Health and Mental Hygiene uses predetermined rainfall limits and notification durations that are set each year for each of its beaches. The department develops the rainfall limits from a multiyear analysis of data from the New York/New Jersey Harbor Pathogens Model, combined with sampling data. The rainfall limits and notification durations were tested and validated in the development phase, and the department reevaluates and updates them each year as needed. The Regional Bypass Model provides the department information about the effects of CSOs, sewage pipe breaks or diversions, and consequential closure time needed. The predetermined rainfall limits are considered to be conservative, and sampling is conducted weekly during the recreation season. The New York/New Jersey Harbor Pathogens Model is also used to develop total maximum daily loads in the New York/New Jersey Harbor.

The 2009 rainfall limits and notification durations are shown in Table 4-4.

Table 4-4. New York City wet-weather advisory information for 2009

Beach	Rainfall limit (inches)	Duration of notification (hours)
South Beach, Midland Beach, Manhattan Beach, Kingsborough CC	1.5–2	12
	> 2.5	24
Orchard Beach	> 2.5	24
Coney Island	> 2.5	12
Gerritsen Beach, Whitestone Booster	0.3–0.6	18
	> 0.6	40
All Bronx Private Beaches	0.6–2.5	36
	> 2.5	48
Douglaston Manor	0.3–0.6	30
	0.6–2.5	60
	> 2.5	72

Milwaukee, Wisconsin

Five public city beaches in Milwaukee are on Lake Michigan, and each beach varies greatly in terms of water quality conditions and characteristics. The water quality near the northern beaches fluctuates daily, whereas the water quality at the southern beaches varies less frequently. The variations are influenced by a combination of nonpoint source pollution, stormwater outfalls, CSO, and the hydrodynamic characteristics of the lake near the beaches. A statistical model of bacterial densities was attempted at the southern beaches in Milwaukee, but it is no longer being used because of poor sensitivity and inadequate funding.

After frequent observations of stormwater outfalls, a rainfall threshold level was established for all beaches. All beaches operate on a threshold of one inch (2.5 cm) of rainfall within 24 hours (data are from the NWS, 7 a.m.–7 a.m. accumulation), which results in a 2-day notification. Milwaukee uses standard signs designed by the Wisconsin Department of Natural Resources to post notifications at its beaches, which are assessed daily. If a sewage diversion occurs, the beaches are closed for 4 days.

Scotland

The Scottish Environment Protection Agency has developed and runs a real-time water quality prediction tool for 10 beaches throughout Scotland. The tool has been in effect since 2004. It uses a set of site-specific criteria for rainfall and river flow to predict water quality on the basis of historical data. Real-time predictions against the current European Union Bathing Water Directive were correct or precautionary on 99 percent of days and correct for 82 percent of compliance samplings during 2007, and 81 percent of compliance samples during the 2008 season (McPhail and Stidson 2009). The revised 2006 directive sets out more stringent bathing water quality standards that require increased model performance. New predictive tools are being developed using decision tree statistical software and are intended to replace the existing prediction tool by 2012. The agency plans to extend the system to additional beaches (about 15 more) by 2012. For more information, visit www.sepa.org.uk/water/bathing_waters.aspx.

4.2.2 Notification Protocol

This section discusses the primary types of notification protocol that are used to predict beach notifications.

Maine

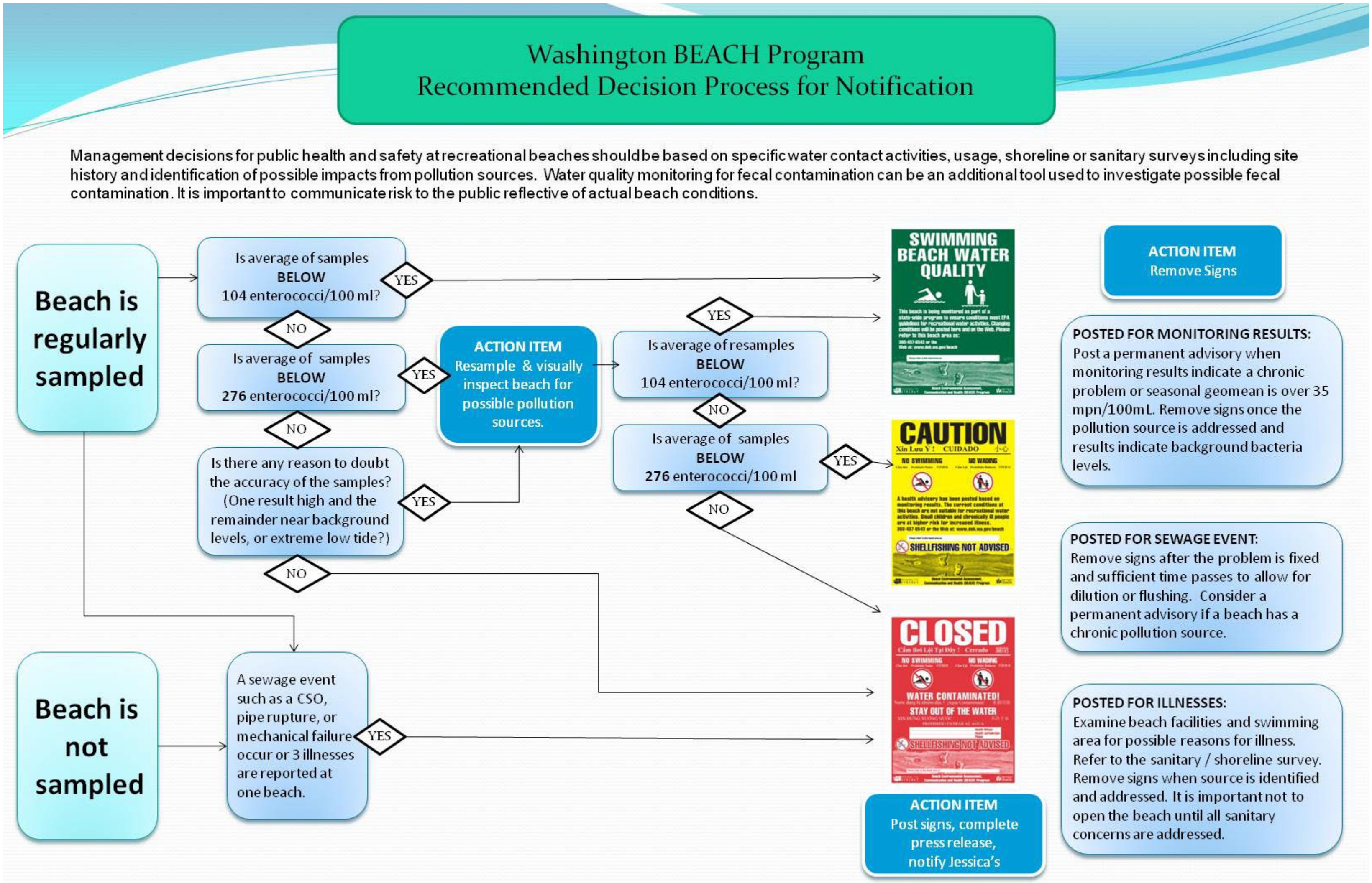
Maine uses sampling and a risk-based assessment matrix (Maine State Planning Office 2004) to determine the beach conditions and the probability of infecting swimmers. The Maine Healthy Beach Program is in the early stages of training beach managers and community members how to assess and monitor beaches. As the program progresses, beach managers and community members will develop rain thresholds to apply to their beaches. Notifications are determined using the assessment matrix, which is shaped to the needs of each beach. The matrix is similar to a sanitary survey, where the assessor looks for certain beach characteristics and pollution sources and either adds or removes points according to conditions. The total score puts the beach into a category that determines what the action would be.

Rhode Island

Rhode Island has implemented notification protocol at two of its highest priority beaches. The state used more than 10 years of water quality data as a foundation for protocol development. The data focus on significant rain events (0.5 in), bacteria monitoring data (criteria exceedances), monitoring frequency, flushing rates, and total closure days. Rhode Island will use the protocols to streamline the beach advisory and notification process.

Washington

Washington uses a flowchart (see Figure 4-1) in addition to regular sampling to assess the conditions of its beaches. Each county develops a process specific to the beaches in its area. Factors influencing the managers' closure decisions include the sampling method, site history, visual inspection, consultation with the beach coordinator, and beach characteristics such as activity/usage frequency (Tiers 1 through 3). The Washington BEACH program also receives information from the state shellfish program, when its model results for shellfish beds indicate that nearby beach areas might be affected.



Source: Washington Department of Ecology

Figure 4-1. Flow chart used in Washington as part of its notification protocol.

4.3 Deterministic and Combination Models

Regional Bypass Model (New York and New Jersey)

Information from the New York/New Jersey Regional Bypass Model is used in combination with monitoring data and historical data to set rain threshold levels and to make beach advisory decisions at many New York City beaches. The net result of tidal and current effects, combined with stormwater outfall data after a rain event is considered each year to determine a rain threshold level for each beach. The model can also be used to determine the effects of a sewage pipe break or diversion. The model is considered conservative, and sampling is conducted weekly during the recreation season to observe the protectiveness of each rain threshold level.

120-Hour Forecasting Model (Michigan)

The beach water quality forecasting model (a decision support system) is being developed to test the ability to predict beach water quality 120 hours into the future using available parameters from NOAA's deterministic forecasting models and forecast data sets (Great Lakes Environmental Research Laboratory [GLERL]/Great Lakes Coastal Forecasting System and the NOAA/NWS National Digital Forecast Database). The model developed for an individual beach using deterministic parameters will be run in an operational forecasting setting by the NOAA/National Weather Forecast Offices where the beach is geographically located with forecast information provided to the Beach County Health Department responsible for beach management. Parameters used by the model are all forecasted by NWS and NOAA-GLERL out to 120 hours in the future. Some of the parameters, for example, are surface and bottom current speed and direction near the beach, wave height, sunlight, wind gustiness, dew point, cloud cover, and rainfall. Data needed from the beach manager are the *E. coli* measurements and time of sampling.

NOAA's GLERL, in Ann Arbor, Michigan, has been developing deterministic forecasting methods that incorporate process modeling (river and lake dynamics) for Grand River, Michigan, and Burns Ditch, Indiana, (http://www.glerl.noaa.gov/res/glcfs/gh/ and http://www.glerl.noaa.gov/res/glcfs/bd/) and forecast input variables (rainfall, wind velocity and direction, and wave height). GLERL is continuing to develop the river and lake model in the Clinton River watershed in Michigan and Lake St. Clair. The lake model will include unstructured variable grid patterns to allow for effective modeling of a complex shoreline. GLERL will advance basic science by modeling the deposition and resuspension of suspended solids in the near-shore zone using resuspension potential based on shear stress and the Grant-Madsen boundary layer model. Resuspension potential can be substituted for turbidity measurements, a key parameter in many Nowcast models.

5 Developing a Beach Notification Statistical Model

Section 2.1 introduces statistical modeling for beach notification decisions. This chapter provides more details on the elements required for developing a statistical model on the basis of a review of available literature. Volume II of this report gives a more detailed discussion of information on data sources, techniques for refining models, advanced statistical methodologies, and specific applications of Virtual Beach software.

5.1 Considerations for Developing a Statistical Model

To develop a statistical model, the beach manager needs an existing monitoring program, a basic knowledge of statistics, and statist l software ica (Francy et al. 2006). Equipment costs for data collection and initial model development are typically not much more than are required for a beach monitoring program, and much of the data required for statistical models are available from other agencies or are easily measured by field staff. Once a model proves to be useful, a beach manager can invest in more expensive equipment to measure environmental conditions in real time.

A statistical software package (such as SAS), Virtual Beach, or Excel can construct a multivariable linear regression equation using a data set containing the necessary data. The result of a multivariable linear regression statistical analysis will be an equation of this generic form:

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + E$$

Where Y, the *dependent* variable, is an FIB measurement; X_1, X_2, and X_3 are independent variables such as turbidity or rainfall amount; b_1, b_2, and b_3 are regression coefficients; b_0 is the intercept of the model; and E is random variation or unexplained error. The Es are assumed to be independently and identically distributed from some distribution (frequently assumed to be normal) with a mean of zero and a standard deviation of σ_E. If Y and Xs do not have linear relationships, both Y and the Xs can be transformed using the log function, the natural log, square root, square, or other transformations to ensure that Y and X have a linear relationship.

Often, models are refined and improved as new data are gathered (Frick et al. 2008). In Ohio, for example, it has been found that splitting the swimming season into two separate periods (early summer and late summer) produces the best predictive models (Francy and Darner 2007). That approach of developing sub-models for complete data sets has also been applied to Huntington State Beach in California, where pathogen dynamics during the wet and dry seasons can be driven by different environmental factors (Boehm et al. 2007). When the model changes over time, i.e., the independent variables important for predicting water quality at a site change over time, statistical techniques like weighted regression (weighting most recent observations the highest) and machine learning might be needed. The actual causal factors behind the temporal changes could be related to watershed development, seasonal differences, climate change, changes in large-scale hydrologic patterns, and so forth. The developers of Virtual Beach software have achieved favorable results at certain beaches by using a *rolling data set*—

developing predictive models using only the most recent 90 days of data, as described in Volume II of this report.

5.2 Selecting Variables for a Statistical Model

Many independent variables might be included in a statistical model, ranging from physical hydrologic measurements (such as turbidity and air/water temperature), chemical parameters (such as DO, pH, and specific conductivity), biological (chlorophyll *a*), meteorological (rainfall, solar irradiance, stream discharge), beach characteristics (number of birds and bathers), and pollution inputs (stormwater, sewage). The following sections provide information about potentially useful independent variables and why they might be included in a statistical model for a beach program.

5.2.1 Physical

Turbidity can be increased by stormwater input or stream inflow, wind speed and direction, wave activity, swimmer activity, and other factors. Some of these factors might be associated with input of pollution (input of stormwater or stream flow), resuspension of bottom sediments (which might or might not be associated with higher indicator counts), or both (for example, swimmer activity). No matter the cause of increased turbidity, if a correlation to FIB levels exists, it is usually a positive correlation.

Water temperature can also be important in assessing the persistence of FIB in the environment, because some are intolerant of extreme high or low temperatures. Unusual water temperature stratifications or large changes in water temperature can be an indication of important water inputs that could carry high FIB loads to the beach (e.g., stormwater or stream flow input).

Sunlight intensity or solar irradiance can also be an important independent variable because some FIB are sensitive to sunlight and might not tolerate high levels.

5.2.2 Chemical

Conductivity is highly correlated with the concentration of dissolved solids in the water column. In a freshwater environment, elevated conductivity could be associated with runoff or effluent from a POTW. In a marine environment, changes in conductivity might be associated with input from a freshwater tributary, POTW effluent, or tidal stage. DO is measured at some beaches and can be associated with a variety of pollution sources. Also, increases in dissolved organic matter and UV absorption coefficients can provide an indication of FIB contamination from tributaries near a beach. pH has also sometimes proven to be a useful predictor of FIB levels. Fluctuations in those or other chemical parameters can indicate surface water inputs to a beach and a potential source of FIB.

5.2.3 Meteorological and Hydrologic

Rainfall data have historically been important in developing predictive tools for beach management. For some beaches, characteristics of antecedent rainfall are the primary inputs needed to predict the beach water quality. In addition to knowing the rainfall volume, the intensity of rain and antecedent dry or wet days are also useful. The rain data can be for specific locations in a watershed affecting a beach, at the beach itself, or at some other monitored rain gauge for which data are available.

Often, a threshold level of rainfall exists beyond which elevated bacteria counts are likely. The threshold varies from site to site and from region to region and is determined through sampling and data analysis. Developing rainfall threshold levels is discussed in Chapter 6.

Conditions that affect surface-water runoff from rainfall include amount and intensity of rainfall, land use and land cover, saturation level of soil, stormwater management systems and retention ponds, and other factors. Intense rainfall, leading to overland flows, can erode soil and stream sediments and transport entrained material, including animal feces.

Wind Speed and Direction

Wind speed and direction can play a crucial role in transporting FIB from a potential source location to a beach. Wind especially influences wave formation. Waves are the main source of energy that causes beaches to change in size, shape, and sediment type. They facilitate movement of debris between the beach and the offshore zone. The three main characteristics of waves are their height, wavelength, and the direction from which they approach. Bacteria in bottom sediments or sand can be resuspended by wave action, increasing FIB levels in the adjacent waters. For example, studies at beaches along the southern shore of Lake Michigan have shown that *E. coli* densities in the sands of the swash zone are high, or higher, than those of the water column (Whitman et al. 1999). When storm winds initiate waves and direct them onto beaches, the foreshore sand is disturbed, and *stored* bacteria are released into the water, raising the *E. coli* densities to levels above the allowable threshold for full-body contact (Whitman et al. 1999; Haack et al. 2002). In such an instance, the sand acts as a reservoir of FIB that might or might not be accompanied by other fecal constituents.

Current Magnitude and Direction

Several studies have shown that the magnitude and direction (alongshore and cross-shore components) of currents strongly influence FIB levels at beaches (Thupaki et al. 2010). A longshore or littoral current runs parallel to the shore as a result of waves breaking at an angle on the shore or as a result of larger hydrologic processes. The speed and direction of the currents can be critical parameters that explain the transport of FIB from a nearby source to the beach.

Tide/Moon Phase

Depending on the location of the beach, the tidal phase can have an effect on water quality. Such information is easy to find and could be a useful, independent variable in a statistical model. Incoming tides are associated with onshore currents, which tend to prevent pollutants from flowing seaward. Tidal flushing of an embayment might occur, moving pollutants out from beach areas. However, in some cases (e.g., physical barriers or structures), tidal flushing can be inhibited. Tidal activity has the potential to affect ambient water quality conditions either by increasing or decreasing FIB levels. The increased range of spring tides has been shown to be associated with increased indicator (enterococci) densities at 60 beaches in Southern California (Boehm and Weisberg 2005). Likely sources of indicator bacteria include groundwater discharges from the beach face as well as beach materials containing FIB such as wrack and bird feces on sand newly inundated by spring tides. High tides also have been associated with elevated levels of FIB at beaches, presumably from resuspension of FIB from contaminated beach sands into the water column (Shibata et al. 2004).

River Flow

Increases in river flow are typically associated with rain events and runoff, and they could be indicative of high pollutant loads. If the beach area is along the river itself, higher flows are typically correlated with higher FIB levels. Flow rate has an effect on the travel time of pollutants moving from a source to a beach and would therefore affect the timing of a potential associated notification.

River Stage

It is well known that a key factor in causing episodes of short-term pollution with elevated FIB densities is wet weather. A rise in the river stage is associated with rain. The river stage is related to the river discharge and velocity. River stage has frequently been found to correlate with bacteria densities or with a likelihood of exceeding the bacteria standard. At 10 beaches in Scotland, a predictive tool has been developed that uses rainfall and river flow to predict FIB densities (McPhail and Stidson 2009).

Lake Stage

The lake stage gives an indication that previous rainfall amounts might have increased the volume of the lake. Rainfall and stormwater flow into a lake is usually associated with increased FIB levels. Inundation of shoreline areas previously unexposed (and suspension of the bacteria harbored in the sediments) can lead to decreased water quality.

Groundwater

Groundwater flow into beach water can carry FIB and enteric viruses from nearby septic systems or leaking wastewater infrastructure. It has been shown at a California beach that microbes can be transported through pore spaces in groundwater (Boehm et al. 2004). Groundwater flow into the system could also be a dilution factor.

5.2.4 Other

Physical Location of the Beach (Bay or Shore)

The geographic setting of a beach should be considered when developing a statistically based model. Knowledge of the location of potential FIB sources and hydrologic attributes of the waterbody, as incorporated in a sanitary survey at a beach, are the basis of beach management including the use of statistical models.

Sampling Methods

Factors such as sampling location, sample depth, and time of sample collection need to be considered for data collection when developing a predictive tool. EPA's Environmental Monitoring for Public Access and Community Tracking (EMPACT) study (USEPA 2005) examines relationships between FIB measurements (using EPA-approved culture methods) and such factors. Because of the predictable differences in microbial counts with spatial and temporal factors, choosing a consistent sampling strategy is important.

EPA found that at three of the five beaches studied, no statistical difference existed among bacteria densities on the basis of samples collected from different points parallel to the beachfront, which spanned a distance of 60 meters, as long as they came from water of the same depth.

The greatest single determinant of bacteria densities was found to be the depth zone (distance from the shoreline at which the sample was collected). Bacterial densities became substantially lower as one moved from ankle-deep to knee-deep to chest-deep water. That has important implications for sample design and for public health. However, the study also found no significant difference in indicator levels among samples that were taken at different depths below the surface, such as between those taken 0.3 meter beneath the surface and those taken near the bottom.

EPA observed significant declines in indicator densities from the morning to the afternoon (9:00 a.m. to 2:00 p.m.) at four of the five beaches investigated in the EMPACT study. That effect was seen only on sunny days at one freshwater beach, but it was observed to be independent of sunshine at three others—a freshwater beach and two marine beaches. Indicator levels at the remaining beach, a West Coast marine environment, tended to be very low at all times.

The EMPACT study was conducted using culture methods. Similar data using qPCR methods are preliminary and not yet available.

Pollution Inputs

Some pollution sources are measureable and could be included in a statistical model. They include agricultural runoff volume during a rain event, stormwater flows, CSO/SSO discharges, number of swimmers/bathers, and the presence of sediment, measured as turbidity or total suspended solids.

5.3 Collecting Data for a Statistical Model

For beach water quality modeling, free, publicly available meteorological data from a nearby airport or weather station will typically form the base or foundation of the independent variable data set. Collecting on-site hydrological (e.g., current direction, gauge height), meteorological (e.g., rainfall, solar irradiation, air temperature), or water chemistry (e.g., turbidity, water temperature, DO, specific conductivity) data requires additional personnel and financial resources. The benefits gained by having on-site data should be considered against the costs of deploying, maintaining, and collecting data from on-site equipment. Volume II, Chapter 2 details an example of such a comparative analysis at South Shore Beach, Milwaukee. Improvements in model accuracy from having additional on-site data are likely to be beach-specific. Microbial data must be collected at the beach. Given the day-to-day variability of microbial data, measurement frequency should be a minimum of several times per week over a period of months to years to develop reliable models (see Frick et al. 2008 and Volume II of this report).

Several options for data collection are available, depending on the needs and resources of the prediction efforts. Automatic samplers are desirable for frequent and regular sampling but might not be useful (except in special situations) for collecting microbial samples because of required holding times and sample degradation. Automated sampling equipment (such as ISCO samplers) has been used to collect water samples for microbial measurements in streams and rivers following rainfall events. Collection by such samplers is initiated automatically by signals from rainfall sensors. Sensors, meters, data loggers, and telemetry can be used to communicate an instantaneous reading to a network system or for readings at regular times when staff are unavailable. Typical USGS gauging stations and those applied in Kansas and Georgia report instantaneous water stage measurements at 15-minute or 1-hour intervals.

Maintaining a full weather station at the beach or at another location for the purpose of developing and operating a predictive tool has been done at several locations in the Great Lakes. In Lake County, Illinois, for example, the data are transmitted via satellite to the office. For information about automated sampling and remote transmittal of data, see Volume II of this report. Maintaining a local river stage gauge is feasible and has relatively low cost. Data can be transmitted via satellite to the office. Managers can intensify sampling efforts for model setup or calibration, and then lessen them as a prediction tool becomes established and proven to be reliable.

The following list summarizes data collection parameters likely to be most useful for developing a predictive tool.

- Possible for automated collection
  - Stream or river: flow, velocity, stage (gauge height)
  - Waterbody: current speed and direction (often measures using Acoustic Doppler Current Profiler equipment), tidal phases, swimmers, wave height, lake level, underwater light sensors
  - Weather: air temperature, wind speed and direction, precipitation, relative humidity, lake stage, water temperature and clarity, solar irradiance (sunlight intensity), and wave height
  - Water characteristics: water quality (data sondes), turbidity, salinity, conductivity, temperature, DO, pH
  - Season, day of year, and moon phase are all easily obtainable
- Field observations
  - Number of swimmers and animals on beach and in swim area
  - Chlorophyll *a*
  - Bacterial indicator
  - Surface water flow conditions (are there visible changes in surface water flow?)

5.3.1 Widely Used Data and Data Sources

5.3.1.1 National Weather Service Weather Station Data

Weather data are frequently available and easily downloaded from local stations and airports in various formats and for different variables. Meteorological weather data can be successfully used for statistical predictive tool development and implementation. The location of a weather station relative to the beach is important. The correlation between meteorology at the weather station and the beach degrades as the distance of the weather station from the beach increases. To find a weather station closest to a beach, use http://lwf.ncdc.noaa.gov/oa/climate/stationlocator.html.

Some variables, such as insolation or solar radiation, which influences the survival of FIB, are not collected at some public weather stations and would therefore have to be collected locally.

Many municipalities prefer to have site-specific weather data collection equipment at the beach to ensure more reliable predictive models. Especially on large lakes and coastlines, weather conditions can be dramatically different on the shore compared to inland.

Historical data of water quality and microbial indicator levels are not as common, but they are very useful if available. A historical data set is useful only if it includes bacterial indicator levels coupled with other measurements and if it is of consistent and of acceptable quality.

5.3.1.2 U.S. Geological Survey Stream Gaging Station Data

The USGS maintains a network of stream gauging stations around the country. To see if a stream is in the network, visit http://waterdata.usgs.gov/nwis/rt. Often, historical data can be downloaded from that site. Data at the stations might include results from occasional bacterial sampling, but rarely will it include results from an established, periodic bacterial sampling regime, unless the station was designated for FIB monitoring under a special project. Station records can include meteorological data, in some cases, and occasionally water chemistry sampling data, such as pH, specific conductance, and DO.

Stream flow data include river stage, and a calculated river *discharge* or *volume* variable. Either of those parameters could prove useful as an independent variable.

Real-time, daily stream flow conditions typically are recorded at either 15- or 60-minute intervals, stored on-site, and then transmitted to USGS offices every 1 to 4 hours, depending on the data relay technique. Recording and transmission times can be more frequent during high flow events. Data from real-time sites are relayed to USGS offices via satellite, telephone, or radio and are available for viewing within minutes of arrival.

5.3.1.3 Data from Sanitary Survey Investigations

Sanitary survey information can help beach managers synthesize all contributing beach and watershed information—including water quality data, pollutant source data, and land use data—so that sources of pollution can be identified.

Sanitary survey investigations will contribute to the knowledge of the hydrologic setting of a beach and can result in information about which data are most important for developing a predictive tool.

Beach sanitary surveys consist of collecting information on contributing sources of water and water pollution in the watershed and gathering information. Depending on the level of detail, the survey can include collecting and analyzing already available information, or it could include new daily measurements and field observations. A sanitary survey provides a documented historical record of beach and watershed water quality. It serves as a baseline snapshot to compare future beach and watershed assessments, and it enables beach managers to perform long-range water quality and resource planning. An official sanitary survey that has been well documented and validated can provide information for prioritizing funds used to remediate and eliminate pollution sources. The information in the survey can benefit stormwater program managers, wastewater facility managers, local elected officials, local planning authorities, academic researchers, and other beach and water quality professionals.

The sanitary survey information collected on Great Lakes beaches has been useful to the Great Lakes states for developing statistical models. That information consists of measurements of turbidity, nearby stream discharge measurements, longshore currents, and regular observations of beach activity. It is important that observations be associated with microbial sampling because that will serve as the response variable when developing a statistical model.

Data collected for a beach sanitary survey can facilitate the development of a predictive tool; however, the purpose of a beach sanitary survey is different from that of a data-collection effort specifically designed for statistical modeling. For that reason, data collected for a beach sanitary survey might not always be useful in predictive modeling.

Information from a sanitary survey can be used to develop a predictive tool in several ways:

- If the pollution source seems to be mostly urban or stormwater runoff or CSOs, developing a rain threshold level might work well and not require as many resources as a statistical model.
- If leaky septic systems abound, sewage overflows occur, or other known sources of human fecal material are present, managers will want to account for such factors in the model or notification protocol.
- If weather conditions (rainfall, wind speed, intensity of sunlight) or water currents affect bacteria levels at the sampling stations, managers should include such conditions in the data-collection efforts for predictive tool development.

5.4 ENSURING DATA QUALITY

Developing and implementing a Quality Assurance Plan is recommended for a beach monitoring program. Managers should develop a plan when developing a data set leading to an effective, reliable predictive tool. Decisions regarding what data are of a useable quality are made when developing a Quality Assurance Plan, which is then followed throughout the project.

Examples of details covered in a Quality Assurance Plan include the following:

- Laboratory methods (laboratories employ different methods, and their detections will vary)
- Laboratory certification requirements

- Sampling protocol (sampling time of day, sampling depth)
- Field sampling procedures and schedule
- Replicate sampling procedure and schedule
- Procedures for data collected by an auto sampler
- Data processing procedures and documentation
- Quality assurance/quality control procedures
- Information on using historical data (when acquiring and using historical data, the quality of the data is important if the data will be compared with newly collected samples)

Data quality guidelines should apply to all data collected, including turbidity, water chemistry, stream gaging measurements, and microbiological sampling data. However, more inherent uncertainty exists within the microbiological samples. That uncertainty is in the sample collection location, the sample collection method, and in the analytical method. For that reason, duplicate sampling or composite sampling protocol can be incorporated into the sampling procedures.

Immediately after data collection, an examination should follow to identify any observations with high leverage or outliers in the data set. Points with high leverage could greatly affect the fitting of model coefficients. An outlier, on the other hand, refers to an observation that markedly differs from the other points in a data set, possibly because of data entry error. Influential points both have high leverage and are outliers.

Figure 5-1 demonstrates those concepts in terms of a simple linear regression of Y on a single X variable. Point A is an outlier. It does not fit the trend mapped by the rest of the data. However, the X value of Point A is very near the mean value of X across the data set, so it would have very little influence on the slope of the fitted regression line. It could pull the line up, thereby influencing the value of the intercept but not the slope. Point B has high leverage, because its X value is much greater than the X values of the other observations. However, it is in line with the trend mapped by the other observations, so it has little influence on the slope or intercept of a fitted regression line. Point C is the most influential point in the data set. Not only does it have high leverage, but it also is an outlier, meaning it does not fit the trend mapped by the rest of the data set. If one includes Point C in the analysis, it would have a large effect on the regression model fit to the data. That observation should be examined closely to determine if it is indeed a valid data point.

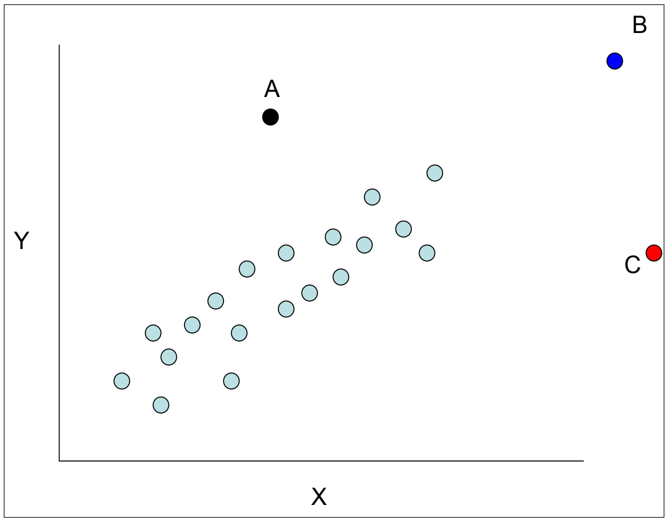


Figure 5-1. Points A, B, and C represent an outlier, a high-leverage point, and an influential point, respectively, in a regression context.

Several statistical techniques are useful for detecting such types of points:

- Index plot of residuals: This is the simplest way to visually identify outliers. The residual measures how far off the general *trend* of the data a given data point lies.
- Index plot of leverages: The average leverage of a data point is *p/n*, where *p* is the number of parameters, and *n* is the number of observations in the data set. As a general rule, any leverage greater than *2p/n* is relatively large and should be investigated further.
- Studentized (either internal or external) residuals: The advantage of studentized residuals over normal residuals is that they have been standardized to have equal variance. An internally studentized residual is based on the residual of a given observation when that observation is included in the data set. An externally studentized residual is based on the residual of a given observation when that observation is removed from the data set before a regression line is fit.
- Cook's distance: This statistic combines the internally studentized residual and leverage value for a data point and, thus, can be used to identify influential points.
- DFFITS: This statistic is similar to Cook's distance, but it is based on the externally studentized residual and as such can more easily identify highly influential points.

Observations identified as extreme values using the above techniques should be noted for further investigation. If highly influential points or extreme outliers are confirmed as stemming from bad data, they should be removed to maximize model accuracy and efficiency.

5.5 Conducting Exploratory Data Analysis

Developers of statistical models should answer a number of key questions using exploratory data analysis before beginning the actual model development. They include the following:

- Are there outliers or high leverage observations, as detailed in the previous section?
- Is the relationship between the FIB densities and the independent variables linear? If not, consider a transformation of any of the explanatory variables to linearize the relationship, or consider omitting the variable.
- Are any pairs of independent variables highly correlated? Such co-linearity can lead to later problems with regression analyses.
- Which explanatory variables have strong univariate associations with FIB densities? In multivariable linear regression, the association of each independent variable is being measured in the presence of the other independent variables in the model. Some independent variables alone would have a strong relationship to the response, but once other independent variables are added to a model, the usefulness of the original independent variable would be minimal. Likewise, two independent variables could interact in such a way that neither is highly correlated to the response alone, but both are highly correlated to the response if they appear in a regression model together. The lesson is to interpret univariate correlations between the response and any independent variables carefully.
- Was the strength of the univariate correlation between the response and independent variables consistent through time?

A statistical model is developed using a water quality data set including FIB concentrations (the dependent variable) and an assortment of independent variables. For each beach, summarize beach data as the data are collected, so that errors can be quickly identified and corrected. Because of their wide range, bacterial densities are generally log(10) transformed before data analysis (Francy 2006) to ensure normality of the measurement. If data are available for one year or more, start by summarizing the data for each year or for years of data combined. Include the median, minimum, and maximum bacterial indicator concentration and the number of days the standard was exceeded. Simple relationships to potential explanatory variables might begin to emerge.

If data are available for less than one year, they can still be analyzed, especially if samples have been taken frequently. Keep in mind that relationships between variables and bacteria densities might not be apparent with a smaller data set. The correspondence between the predictions of the statistical model and actual observations at the beach is the final proof of model efficacy/reliability. The model is best evaluated using a data set outside the one used to develop the model (Frick et al. 2008; Boehm et al. 2007). Developers of Virtual Beach used data sets as small as 25–30 data points over a period of 60 days, or approximately a single swimming season (Frick et al. 2008). Evaluation of models is covered in Volume II of this report).

Next, examine scatter plots of all measured independent variables versus bacteria densities. If a continuous linear relationship is apparent in the scatter plot, the constituent could be useful as a predictive variable. If the relationship is continuous but nonlinear, try transforming the variable using a second-order polynomial, square root, logarithm, or inverse. If a linear relationship is still not apparent after transformation, consider expressing the variable in categories or omit the variable from consideration in the model. For variables that might not be continuous (cloud cover, wave heights), use box plots to summarize mean responses by category. Analyze plots by year and for all years combined (Francy 2006).

Before the multivariable linear regression model development phase proceeds, check the data set to determine if it includes explanatory variables that are strongly related to each other (co-linearity). If such pairs of independent variables exist, consider using only one in a multiple linear regression model because high co-linearity among the independent variables leads to poorly estimated regression coefficients. A general rule is to be cautious about correlation coefficients that exceed 0.80. Often, the choice of which of the pair to retain for analysis comes down to deciding which one is easiest or cheapest to measure or interpret.

Although not discussed in this volume, Boehm et al. (2007) have provided evidence that the partial least squares modeling approach does not require that the independent data sets be uncorrelated. Additional work is required to determine if the partial least squares approach can be generalized.

5.6 Developing Your Statistical Model

This section is a compilation of published and unpublished methods of developing a statistical model for predicting beach advisories. Many of the recommendations come from publications of the Ohio USGS and from the EPA developers of Virtual Beach. After constructing a set of independent variables, a statistical software package such as Excel, Virtual Beach, or SAS can be used to initiate multiple linear regression model development evaluation.

Several metrics can be used to measure model goodness-of-fit or explanatory power. The coefficient of determination, R^2, was historically used as the primary determinant of model fitness. The R^2 value summarizes the percent of the variability in the response variable that can be attributed to the variability in the independent variables. Values of R^2 can vary from 0 (no variability explained) to 1 (all variability explained).

Statisticians recognized a flaw in R^2, however. It always rises as more parameters are added to the model. At some point, a model becomes over-parameterized—meaning the ratio of explanatory parameters to data observations is too low. An over-parameterized model can closely fit a set of training data (i.e., data used to generate the model), but it poorly predicts any new observations outside the original data. In essence, it is too tightly tailored to the training data.

To counteract that phenomenon, statisticians developed new metrics that include a penalty for adding parameters. The adjusted R^2 is one such measure, as is Mallows' Cp (Mallows 1973; Frick et al. 2008), Akaike's Information Criterion (AIC) (Akaike 1974), and the Bayes Information Criterion (BIC) (Schwarz 1978). Those metrics attempt to maximize the amount of explained variability in the response variable while relying on a minimum number of parameters in the model, thus avoiding over-fitting. If the modeler adds a parameter to an existing model, and the parameter does little to reduce the unexplained variability in the response variable, the metrics will identify the parameter as relatively useless. In comparing two models using Mallow's Cp, AIC, or BIC, the model with the smaller metric has a better fit to the data, the same fit with fewer independent variables used, or both. The metrics vary in how severely they penalize additional parameters. In general, the order from least to most severe is as follows:

$$\text{adjusted } R^2 < \text{Mallow's Cp} < \text{AIC} < \text{BIC}$$

There is also a *corrected* AIC (McQuarrie and Tsai 1998), which fits between the AIC and BIC in terms of penalty severity. Model developers who choose to use the adjusted R^2 as their selection criterion will likely end up with larger models than if they had used the BIC as their criterion.

In the model-selection process, modelers should consider the selection algorithm in addition to the selection criteria as discussed above. One can choose from backward elimination, forward selection, or stepwise procedure.

- Backward elimination: Start with the full model including all predictors, then remove the predictor with highest p value greater than the significance threshold (usually 0.05). The process is repeated until all p values are less than the significance threshold.
- Forward selection: Start with no variables in the model, then add the predictors to the model one by one based on their p values. Choose the one with lowest p value less than the significance threshold. The process continues until no new predictors can be added.
- Stepwise procedure: This is a combination of the backward elimination and forward selection algorithms. At each step, a variable can be added or removed; any removed variable still has a chance to reenter the model.

Models can be ranked according to any one of the criteria using one of the model-selection algorithms, and the *best* models are then selected for further examination.

5.7 Assessing and Refining Your Statistical Model

Given a candidate *best* model, it is important to analyze the residuals of that model to ensure an important assumption of regression analysis is being met. Multivariable linear regression assumes that the residuals are independent and identically distributed. A plot of the model's residuals versus the fitted values of the response should indicate no obvious pattern (Figure 5-2).

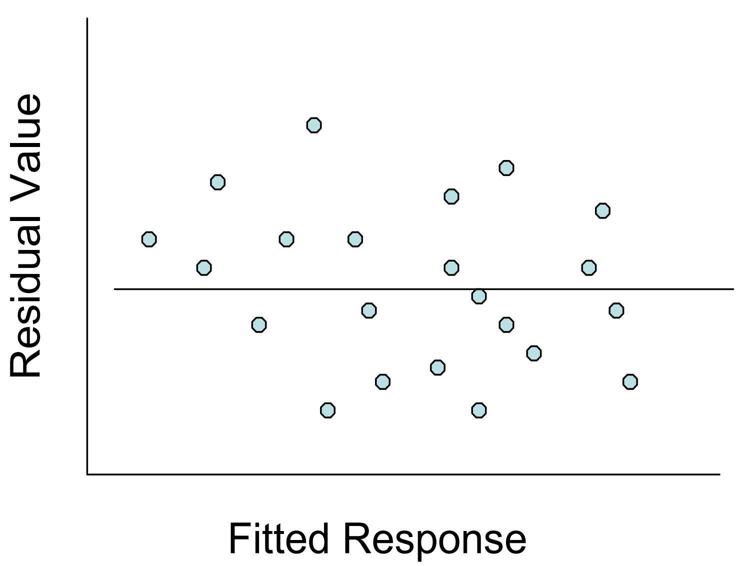


Figure 5-2. An ideal residual plot for a multiple linear regression model showing no discernible pattern among the residuals.

If a non-constant variance is evident in the residuals (Figure 5-3), the Box-Cox transformation can be used.

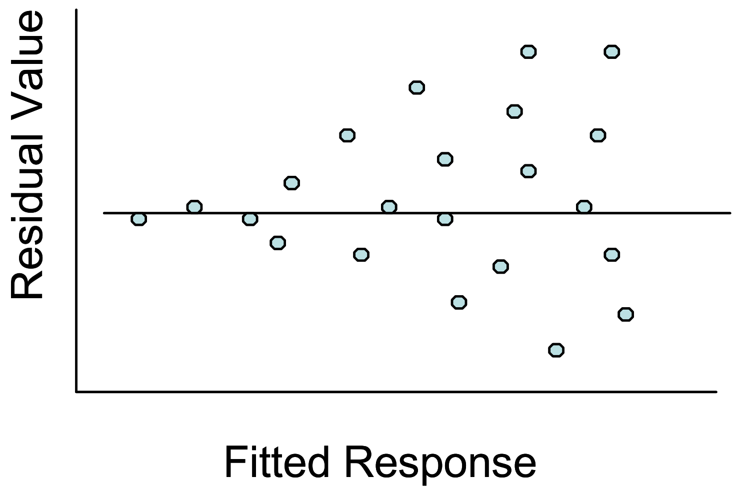


Figure 5-3. A plot of regression residuals that shows indications of heteroscedasticity and the need for a Box-Cox transformation.

The Box-Cox method transforms y into $(y^{\lambda} - 1) / \lambda$, where the value of λ is determined by an iterative algorithm (Box and Cox 1964). The goal of the procedure is to find λ such that the model residuals have equal variance across the range of the fitted values (i.e., they appear as in Figure 5-2, rather than as in Figure 5-3, where variance increases as the fitted response gets larger).

Once the residuals of the candidate model are shown to be independent and identically distributed, the next step is to quantitatively assess the accuracy of model predictions. Such an assessment would ideally use data other than that used to develop the model. The data used to generate the model are called the *training* data set, while the *testing* data are used to assess model predictive accuracy.

Because the statistical model will be used for making public health decisions, the most critical assessment question asks if the model can make correct decisions to post beach notifications (a notification is defined as either an advisory or a closure). In a multivariable linear regression, the total proportion of variability in the response explained by all independent variables in the model is expressed as R^2, and if the model is applied to the testing data set, it could be used as a measure of the predictive strength of the model. Another test of model performance is to examine the number of Type I and Type II errors. A recommendation to close a beach when there is not actually a threshold-exceeding density of bacteria (a Type 1 error, or *false positive* result) would be considered conservative from a public health point of view. However, false positives deprive the would-be swimmer of the enjoyment and use of the beach and can have adverse economic effects on business owners in near-beach locations and erode public confidence in public health decisions. Type II errors (or *false negatives*) result in beaches being opened (or not having a notification in place) when bacterial levels actually exceed the standard. By evaluating how many false positive and false negative predictions a model produces (or the percentage of errors compared to correct predictions), the analyst can begin to determine if the model is indeed *good* enough for reliable use.

In addition to evaluating model performance on the basis of a comparison of model predictions with known measurements, the model's performance should also be compared against a basic and commonly applied method used for assessing recreational water-quality—the persistence model. That model uses the most recent bacterial measurement (typically from the previous day) to predict today's water quality.

Factors that influence the fate and transport of FIB to a specific beach site can change over time. Land use alterations, degradation or improvements to infrastructure, adding near-site sources, and other conditions can cause shifts in the underlying processes driving FIB densities. Even without ostentatious changes in the watershed or near-site geography, one should continually monitor model performance for signs of degrading performance through time.

5.8 Implementing Your Statistical Model

How are the outputs from predictive tools used in decision making? Model developers and beach managers, who consider protecting public health their top priority, continue to creatively address that important question.

Model outputs can be estimated FIB densities, a probability that the water quality standard will be exceeded, or a daily notification status that is to be posted. Chapter 4 provides an overview of several beach models in different stages of use. In the case of the Nowcast model developed by the USGS in Ohio, a *probability threshold* is set for decision making (e.g., at 25 percent probability of exceeding the water quality standard, close the beach). Such probability thresholds can be adjusted and refined to maximize the number of correct predictions or to minimize false negative or false positive outcomes. At those Ohio sites, water quality sampling continued during model development so that decision accuracy could be tested. Given the low threshold (25 percent rather than 50 percent or higher), an emphasis was clearly placed on minimizing false negatives so that public health would be protected. The process of model development, implementation, validation, monitoring, and refinement is used not only for multivariable linear regression analyses, but also for other models of any type as a groundwork for predictive tool implementation.

5.9 Additional Resources

Procedures for developing a statistical model are outlined in the USGS document, *Procedures for Developing Models to Predict Exceedances of Recreational Water Quality Standards at Coastal Beaches* (Francy and Darner 2006). Donna Francy and others with the USGS in Ohio have published work regarding the Nowcast system of predicting and forecasting, as have Richard Whitman and others with the USGS in Indiana, regarding their work in Indiana and Illinois. Olyphant and Pfister (2005) also published work for the Swimcast model in Lake County, Illinois. Those are all good sources of information. Another good source on developing a statistical model is Chapter 9—Nowcasting recreational marine environments (Boehm et al. 2007)—in S*tatistical Framework for Recreational Water Quality Criteria and Monitoring* (Wymer 2007). That chapter discusses predictive variables that should be considered in marine environments, and statistical methods other than multivariable linear regression models (e.g., Partial Least Squares Regression) that should be considered. Language conventions used in this report might differ slightly from other publications. Those resources will provide more technical and detailed information than is covered in this report.

6 Developing Rain Threshold Levels and a Rain Notification Protocol

Many beach managers have noticed a relationship between the concentration of FIB at a beach and the amount of rain received in nearby areas. That relationship can be quantified as an amount or intensity of rainfall (a threshold level) that is likely to cause exceedances of water quality standards at a beach, and the length of time over which the standards will be exceeded. Rain threshold levels can be used as the basis for a beach notification.

Beach managers can also develop a series of questions, or a *decision tree*, considering factors other than rainfall, to guide beach notifications. Such evaluations use water quality sampling, rainfall data, and other environmental factors that could influence the FIB levels, such as proximity to pollution sources, wind direction, visual observations, or other information specific to the region or beach. In this document, that process is referred to as developing a notification protocol.

Exceedance of a predetermined rain threshold level might be one piece of data that is considered in a notification protocol, or it might be the only piece of information considered in a notification protocol.

Guidelines developed by the beach manager should allow for consistent decisions resulting from protocol that can be repeated and tested to determine, for a rainfall event, whether a beach should be placed under a notification. The guidelines might also recommend how long the notification should persist and when follow-up sampling for FIB should occur. Some examples of places that have notification protocol are given in Section 4.2.

The process of developing a rain threshold and notification protocol has three steps:

1. Collecting data for rain threshold levels and notification protocols
2. Developing a rain threshold level
3. Developing a beach notification protocol

6.1 Collecting Data for Rain Threshold Levels and Notification Protocols

To develop rain threshold levels and notification protocols, a large amount of site-specific data on rainfall amounts and FIB sampling results is needed. The investigator must either install a local rain gauge or select a rainfall station that adequately represents local conditions affecting the beach. That technique, at its foundation, assumes that the magnitude and duration of rainfall determines surface water runoff and, thus, FIB loadings to the beach. Data from several rain gauges can be compared before choosing the one whose data best relate to on-site FIB measures.

Key rainfall characteristics when developing rain threshold levels include the following:

- Amount of rainfall
- Storm duration

- Intervening periods expressed in dry days
- Lag time between rainfall record event and receiving beach response
- The season/times of year when the beach receives the most use

Meteorological stations commonly collect and submit daily or hourly data. Hourly stations are preferred especially when dealing with small- to medium-sized watersheds. Additional factors that can be incorporated into the decision protocol include river or lake stage, tide, and current information.

When initiating development of a rain threshold level, it is important to understand wastewater and stormwater infrastructure affecting a beach. Some good questions to ask are as follows:

- Is the sewer collection system combined with the wastewater collection system and routed to a WWTP? If so, what is the level of treatment?
- What is the capacity of the WWTP?
- How often is that capacity exceeded and what amount of rainfall causes that exceedance?

If an amount of rainfall produces a stormwater volume that exceeds the capacity of the WWTP, parts of the treatment process can be bypassed. In watersheds where stormwater is not routed through a WWTP, stream surges can be evident after even small rain events, transporting contamination accumulated on the land surface since the last rain. Flow from a combination of such infrastructure scenarios can contribute to FIB loadings at a beach. It is important to also determine if the impacts of rainfall and loadings have a strong seasonal component and, if so, why that might be the case.

FIB data supporting the development of rain threshold levels are generated from water column densities obtained from ambient or targeted monitoring programs. FIB densities can be used in the analyses as direct observations or can be transformed as geometric mean values. Transformation of FIB observations before developing regression models or exceedance analyses can allow direct comparison to state water quality standards for recreational uses. A rain threshold level can be developed for one or several FIB species. Fecal coliform, *E. coli*, and *Enterococcus* bacteria are common indicator species used in those models.

For relatively small watersheds, it is common to use a single rainfall station selected to be representative of storm conditions experienced by the upstream drainage area. The investigator selecting a representative rainfall station takes into consideration its location in the watershed and its ability to capture the most dominant rainfall events (magnitude and duration) that could generate relatively high storm runoff volumes and transport FIB loadings to the beach. For example, in Delaware, the Department of Natural Resources and Environmental Control selected a rainfall station because of its central location in the watershed and strong statistical correlation with observed FIB densities at the beach site of interest (Delaware Department of Natural Resources and Environmental Control 1998).

When dealing with nonpoint-source-dominated systems, antecedent rainfall conditions can be very significant factors in explaining the relationship between rainfall and FIB densities. Kuntz (1998) found higher FIB densities during periods of low rainfall or near-drought conditions than during seasons of normal rainfall. However, Ackerman and Weisberg (2003) found that an antecedent dry period in Southern California had a minimal effect on FIB levels, given the same storm intensity. Storm event duration might also be a key factor in explaining rainfall-water quality relationships. For a watershed in Delaware, an examination of the relationship between cumulative rainfall over two different durations (24 and 72 hours) and FIB densities shows that the 24-hour cumulative rainfall data yield a statistically stronger relationship than the 72-hour cumulative rainfall data (Delaware Department of Natural Resources and Environmental Control 1997).

6.2 Developing a Rain Threshold Level

6.2.1 Frequency of Exceedance Analysis

Frequency of exceedance analysis is a rainfall-based method that is used to develop rain threshold levels (also called rainfall-based alert curves). A rain threshold level is the smallest amount of rainfall likely to result in an exceedance of the water quality standard. A realization or prediction of that amount of rainfall would trigger a beach notification. Such a method can be applied to situations only in which historical rainfall data and corresponding FIB data exist. After establishing a relationship between rainfall amounts and FIB densities, developing guidelines or a decision protocol for a beach notification is the next step.

Analyzing rainfall data by storm events and identifying a representative data set yields storm characteristics to consider in developing a rain threshold level (e.g., station location, storm duration, intensity, antecedent conditions). Once a representative data set has been obtained, divide the total amount of rainfall over a certain period into segments that range from no rainfall to an upper limit representative of the rainfall record, type of storms, and season. For each rainfall volume category, compare the observed FIB measurement to the water quality standard.

As with any model, the rain threshold level should be validated by testing predictions at beach locations of concern. Those validation exercises will aid in selecting the most appropriate rain threshold level.

6.2.2 Regression Modeling

Another way to develop a rain threshold level is using a simple linear regression (a single independent variable) relating FIB levels to rainfall amounts. Rainfall-based regression models require relatively large monitoring data sets of both rainfall and FIB densities. The basics of that process are described in Chapter 5.

6.3 Developing a Notification Protocol

The rain threshold level is used along with other site-specific information to develop the notification protocol for a beach. Some examples of ancillary information to be considered are observational data (e.g., indications of WWTP bypass), communications with WWTP managers, wind direction, tidal phase, river stage, long shore current direction, and season. Decision protocol will typically specify the conditions requiring a beach warning/notification, closure, or increased water testing.

Because of the seasonality of recreational activities and rainstorm characteristics, rainfall threshold levels and notification protocols can be developed for targeted seasons. Developing predictive tools for various seasons can significantly enhance the predictive capability of the tool. Milwaukee developed beach closure rules on the basis of an analysis of fecal coliform and *E. coli* densities collected daily (Monday–Friday) during the June–September season (City of Milwaukee Health Department 1998). Another example of this is Ohio's model for beaches on Lake Erie. One model is applied for early summer, and another model has been found to be most effective for late summer (Francy 2009).

Consider whether the decision protocol is still in the *information collection phase* or in the *implementation phase*. If it is in the information collection phase, decision protocol performance should be tested frequently and opened for readjustment as needed. In the implementation phase, performance testing does not need to be as frequent unless a significant change in conditions has occurred. Once in the implementation phase, establish a schedule for testing and reevaluating the decision protocol and for recording performance results.

7 Common Challenges and Obstacles

A review of predictive tools for beach notifications reveals different challenges for each beach. Several beach managers have expressed concern that predictive statistical models are cost prohibitive because they require a commitment of resources (data collection, use of software, expertise) and there is no guarantee that a useful predictive tool will be produced. Efforts to develop statistical models in some locations have been aborted. Table 7-1 provides a collective list of challenges and problems reported with predictive tools.

Table 7-1. Issues concerning statistical predictive models and tools

Model setup	Model application	Administrative concerns
• Difficulty in achieving good calibration, degree of accuracy, or correct predictions needed • Determining necessary inputs • Establishing nearby rain gauges • Intensive sampling to explore and establish statistical correlations • Additional sampling required for validation period • Necessary monitoring equipment • Computer programs for analysis (statistics software package) • Long period for setup • Unknown outcome of model accuracy before necessary funding • Water quality standard exceedances inconsistent or sporadic, not enough data for the times when FIB levels are high	• Monitoring equipment for inputs requires maintenance • Challenges placing equipment in secure and meaningful location • Accuracy of prediction and accuracy of analytical method • Staff is still needed to take samples • Prediction accuracy varies depending on environmental (weather) conditions • Model recalibration is necessary for changes in infrastructure and land development	• Knowledgeable staff are needed to understand and run the model • Expertise is needed for model development and maintenance • Equipment, sampling, staff costs • Public confidence • Staff time used in sampling procedures • Communication and storage of data, if data loggers are used

Collective experience suggests that statistical modeling will improve when paired with an enhanced understanding regarding the relationships between weather conditions and bacteria residence time, source-concentration, and water flow directions and hydrology at the beach and in the contributing watershed. Managers of the most successful models discussed in Chapter 4 have documented and understood pollutant sources and how they are manifested at their beaches (e.g., Valley Creek at Port Washington Beach, stormwater outfalls in New York City). Having a good understanding of the important sources and relevant fate and transport mechanisms can greatly improve model prediction accuracy, especially if that knowledge can be used to direct data collection efforts. In some cases, developing a statistical model leads to identification of control measures or correction of infrastructure problems. Even though complex physical, biological, and chemical processes are being represented by a relatively simple statistical relationship, model accuracy can be augmented if the important environmental processes are considered, leading to the monitoring and data collection of useful explanatory variables. Rain threshold and river stage models have proven histories because clear and direct relationships exist between measurable inputs (e.g., rain, turbidity), and measured FIB densities.

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8 Beyond Statistical Modeling

The theme of Volumes I and II of this report is using statistical models and other predictive tools to produce timely estimates of water quality at beaches.

Different types of statistical models are used successfully at many beaches. Development of deterministic models has also advanced. In deterministic models, algorithms are applied that reflect natural processes such as sediment resuspension as they are understood. Deterministic models typically require expertise to implement and would likely be challenging for local beach managers or public health agencies to set up, run, and achieve the accuracy and reliability needed for protecting human health.

An important distinction between statistical models and deterministic models is that in a statistical model, the relationship between water quality and the predictive variable does not have to be understood. In deterministic models, the system being modeled must be fully or partially understood, because applying modeling algorithms that reflect natural processes is what makes them work. Blending the performance of statistically based models with the ability of deterministic models to account for complex variations in circumstances can improve the successful use of statistical models in making accurate and timely predictions of high bacteria levels or water quality standard exceedances.

Researchers are making advances in predictive tool development throughout the United States. The advances are in the areas of data collection and telemetry, data sources, selecting independent variables, quantifying natural processes, statistical methods, computing technologies, and understanding hydrological influences. Components of models are being advanced and fine-tuned at such a rapid pace that it is difficult to capture all developments in this chapter.

8.1 Forecast Modeling

The prospect of days-in-advance forecasts of beach water quality raises the endeavor to a new level. Being able to incorporate forecasting technologies into the process of making beach water quality decisions further increases the utility of predictive modeling to the beach-going public.

Weather forecasting is a core activity of NOAA and is one that is itself based on the use of many models, including deterministic predictive meteorological models. NOAA forecasts include predictions for many of the variables known to directly or indirectly influence water quality at beaches (cloud cover, precipitation, wind velocity, and direction). Using available forecasts for current speed and direction, water and air temperature, wave height, precipitation, stream or river stage combined with knowledge from other models, it is hoped that beach water quality will soon be forecasted in the Great Lakes. NOAA is collaborating with USGS, EPA, and state agencies to develop a system for water quality forecasts at any swimming beach. The system will involve weather predictions from NWS, hydrodynamic predictions from the Great Lakes Environmental Research Laboratory, and site-specific factors for individual beaches (Schwab and Bedford 1994). For more details on the system, visit http://www.glerl.noaa.gov/res/Centers/HumanHealth/near_shore.html.

8.2 REGIONAL MODELING

In general, statistical models and rain threshold level determinations are beach-specific. It would be beneficial if the techniques could apply to a larger geographic area such as a shoreline of several miles or more. On the southern shore of Lake Michigan, NOAA's regional model is being combined with locally collected beach information to enhance predictive capabilities on a regional level.

8.2.1 Great Lakes Finite Element Nested Models

In the mid 1990s, NOAA developed a 5-kilometer-scale finite element model of all five Great Lakes. The model was calibrated to yield real-time predictions of three-dimensional water particle velocity; the three-dimensional temperature field; the water level distribution and the wind-wave height, length, period, and direction; and resuspension, transport, and deposition of bottom sediments on the basis of wave and current conditions. Inputs to the model were provided by satellite feed of NOAA weather data (Schwab and Bedford 1994).

NOAA, USGS, Ohio State University, and EPA researchers have applied and calibrated 100-meter grid nested models in NOAA's 5-kilometer-scale finite element model of Lake Michigan at three locations to provide greater resolution to the effects of stream discharge plumes on nearby beaches. Water quality at Grand Haven State Park and other beaches in the vicinity of the mouth of the Grand River is overwhelmingly influenced by the direction of the plume from that major river, which carries the discharge from a watershed of more than 5,000 square miles. The application and calibration of the nested 100-meter grid in that setting provides real-time updates on the trajectory of the discharge plume four times a day (Schwab and Bedford 1994).

Several statistical models in southern Lake Michigan use outputs such as wave information and current direction from the model, exemplifying how data from a deterministic model can provide input data to a statistical model.

8.3 HYDRODYNAMIC AND FATE AND TRANSPORT MODELING

Nevers and Boehm (2010) provide an overview of using deterministic models to predict FIB densities in surface waters. Nevers and Boehm underscore the value of fate and transport models for increasing and refining the understanding of mechanisms that lead to observed variations in water quality but that are not well defined. That would be of value in instances where the characteristics of a site produce poor or counterintuitive empirical relationships or sites where statistically based models, or decision tree models, fail to achieve satisfactory results. The authors also provide guidance on parameterization of many mechanisms applicable to fate and transport modeling of fecal indicators including advective flux, dispersion, inactivation, growth, predation, adsorption/desorption, deposition/resuspension, and loading. Their work also discusses empirical statistical models as described in Chapter 5 of this report.

8.3.1 Hobie Beach

Hobie Beach, near Miami, Florida, used a deterministic model to further investigate observed contamination problems for which no apparent cause had been identified. At the site, elevated indicator bacteria densities had been a recurring problem, despite the absence of any identified specific point source of pollution. Researchers at the University of Miami (Zhu 2009) employed a predictive numerical model of water column proxy densities for a nonpoint source recreational marine beach. In the first of two phases, the model was used as a tool to investigate microbial processes and source functions and the relationship between observed indicator densities and identified sources in historic data sets. The microbial process model was based on the combined application of hydrodynamic and advection-diffusion equations for transport and mixing. The model calculated the reduction in culturable indicator bacteria densities as a first-order decay process solely on the basis of sunlight deactivation.

Quantitative estimates of enterococci loadings from human shedding and animal fecal (avian and canine) inputs were integrated with beach-use data to estimate the source strength and timing. Model simulations illustrate the transient concentration plumes associated with heavy bather use and animal fecal input events. Model outputs also include current vectors at varying tidal stages and flow conditions. The outputs of the model show that the source of high FIB densities at the beach were from a nearby dog beach. That has clear implications to beach management so that water quality problems could be avoided. Deterministic models such as this might be applicable in a variety of settings without the requirement of an extensive data history (Zhu 2009).

8.3.2 Other

The Nevers and Boehm (2010) report also addresses the uses of deterministic model functions in quantitative microbial risk assessments, which are stacked deterministic models that include fate and transport models along with modeling the infectivity of various pathogens for which epidemiological data are not available.

8.4 New Use of Existing Data and Innovative Analysis

8.4.1 Use of Hydrography (NHDPlus Network) and Land Use Data

In a project conducted in 2007–2009, Research Triangle Institute (RTI 2007), under contract to EPA, integrated calculated outputs from the NHDPlus geospatial data with a statistical model to relate watershed and waterbody characteristics to possible sources of pathogens that can affect water quality at a beach. RTI developed a multivariable linear regression model that relates characteristics of a river flowing into the ocean near the beach to water quality at a beach influenced by the outfall of that river. It incorporates explanatory variables from NHDPlus (elevation-based catchment for each flowline in the stream network, cumulative drainage area characteristics for example), calculated time of travel from potential watershed sources, and publicly available meteorological, marine, beach, and flow data.

The project employs an SAS-based regression system to facilitate a multivariable linear regression analysis. The system was applied and tested at several sites for which adequate data sets were available:

- Santa Barbara, California (coastal)
- Sunset Beach, Oregon (coastal)
- Little Calumet Watershed, Indiana (freshwater)
- Huntington Beach, Ohio (freshwater) (also a Virtual Beach site)

RTI's approach achieved results comparable to applying statistical relationships using other available data and other statistical regression software. As with most predictive models, the best results in terms of correct predictions were obtained with data from the intensively monitored sites over short periods. Although including time of travel information from potential watershed sources did not improve model performance as measured by R^2 in most settings, results were obtained with good performance in terms of false negatives, false positives, and correct predictions, and using publicly available data.

Routine monitoring data for FIB were made available to model developers, and no data were collected specifically for the purpose of developing the predictive model. RTI's approach is a good example of broadening the range of potential predictive variables for regression models by using publicly available data from NHDPlus. Applying watershed land use data and calculated river hydrology characteristics as sources of empirical model inputs is an innovative approach.

8.5 NEURAL NETWORKS AND GENETIC ALGORITHMS

An artificial neural network (ANN) is a construct of software that partially mimics the workings of a biological neural network. ANNs are often applied as nonlinear statistical data modeling tools. They can be used to model relationships between inputs and outputs or to find patterns. The technique is often useful when relationships between inputs and outputs are complex and not clearly understood. An ANN learns relationships between inputs and outputs using a learning algorithm.

ANNs have been used in a handful of studies for predicting pathogen and pathogen indicators in recreational beach and watershed surface water. He and He (2008) successfully used ANNs to predict FIB at marine recreational beaches receiving watershed baseflow and stormwater runoff in Southern California. Mas and Ahlfeld (2007) observed that ANNs performed better than ordinary least squares and binary logistic regression methods for predicting surface water fecal coliform concentrations in a mixed land use watershed. Jin and Englande (2006) used ANNs and logistic regression to predict swimmability for a brackish waterbody. They observed that ANNs performed better than logistic regression especially when conditions were not safe to swim. However, ANNs were successful in forecasting not safe to swim conditions only 53.9 percent of the time. Jin and Englande note that the poor performance was probably because most of the data used in developing the model were collected during safe to swim conditions.

Genetic algorithms are search methods inspired by evolutionary biology. The algorithms are based on techniques such as inheritance, selection, crossover, and mutation used by nature for evolution of species. While genetic algorithms cannot not be used directly for modeling beach pathogens, they can be used to evaluate and select models developed by other modeling techniques. For example, as the number of independent variables increases, the number of possible models to be evaluated by multivariable linear regression increases geometrically resulting in degraded computer performance. In such cases, genetic algorithms can be used to assist multivariable linear regression. Rather than evaluating every possible model, genetic algorithms would intelligently select models to be evaluated, resulting in fewer models needing evaluation. The objective of genetic algorithms is to select the near best model as opposed to finding the best model. The newer version of Virtual Beach uses genetic algorithms to assist multivariable linear regression in reducing the number of models to be evaluated when the number of independent variables is large.

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