Environmental Health/Occupational Health/Injury
Climate and Health

SYNDROMIC SURVEILLANCE CLIMATE AND HEALTH GUIDANCE DOCUMENT

How Jurisdisctions Can Use Surveillance to Quantify and Track Climate-Related Health Impacts

CSTE
COUNCIL OF STATE AND TERRITORIAL EPIDEMIOLOGISTS

ISDS
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Syndromic surveillance climate and health guidance document

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I: INTRODUCTION

A broad range of adverse health outcomes are associated with the changing climate [Moulton 2017; Luber 2014]. Examples include but are not limited to: exacerbations of chronic conditions such as cardiovascular or respiratory diseases, diseases and injuries associated with natural disasters, increased presentation and differing distribution of vector-borne and zoonotic diseases, heat- or cold-related illness, and mental health outcomes associated with displacement and interruption of care [Hess 2009, Schulte 2009; Crimmins 2016]. Adverse outcomes may also arise from climate change adaptation and mitigation efforts, such as increased injuries to pedestrians and cyclists if non-motorized transport is promoted without concurrent increases in infrastructure (e.g., bike lanes or sidewalks) [Pucher 2003; Pucher 2010; Zegeer 2012].

Researchers and applied public health practitioners from many disciplines are working to minimize the changing climate's impact on population health and well-being. This includes but is not limited to: identifying the current risks and vulnerabilities [Manangan 2014], modeling the future risks and vulnerabilities [Kintziger 2017], and creating and implementing adaption and mitigation strategies [Anderson 2017]. For public health practitioners, surveillance is a key activity used to protect and improve the health of the populations they serve. Surveillance can be defined as "the continuous and systematic collection, analysis, interpretation, and dissemination of data to be used for public health action (e.g., policy, planning evaluation)" [Pascal 2012; Porta 2008]. In general, data from public health surveillance can be used for short- and long-term planning and response through retrospective data analysis of trends over time or specific events [Hall 2012]. Combining health outcome data (e.g., hospitalizations or deaths) with environmental and socio-demographic information also provides a more complete picture of most vulnerable populations. However, a recent article noted that climate and health surveillance in the United States (U.S.) was still in the embryonic phase [Moulton 2017]. Therefore, **the goal of this document is to encourage surveillance improvements by providing a general instruction on how a jurisdiction may use their syndromic surveillance systems for climate and health surveillance.**

Climate is the long-term variation in weather patterns, typically over decades [Walsh 2014]. However, for the purpose of public health surveillance, the word *climate* used in the phrase *climate and health* encompasses both short-term meteorological events (weather-related), such as a flood or a winter storm, and long-term meteorological influences (climate-related), such as droughts and increased wildfire activity due to decades of warmer temperatures [Joyce 2014]. As part of the response to climate-related impacts, data from public health surveillance systems are already being used, in some jurisdictions, as the basis for modeling future disease burden and implementing climate change adaptation work [English 2009; Hess 2015].

Syndromic surveillance systems can be a valuable tool for climate and health surveillance. As opposed to traditional surveillance data sources (e.g., hospital discharge data or death certificates) which may have long lags before the data become available, syndromic surveillance systems use (near) real-time health-related data for the early identification of disease outbreaks, disease trend monitoring and the tracking of adverse health outcomes related to an event [ISDS 2012]. This approach allows for rapid response by public health professionals including situational awareness, which may inform an ongoing response, help to activate a response, or potentially determine how response resources are distributed [ISDS 2012]. For instance, in the aftermath of Hurricane Irene (2011), the North Carolina Public Health Department used their syndromic surveillance system to identify an increase in heat-related illness associated with power outages [Personal Communication: Lauren Thie L, NC Department of Public Health, May 2017]. Vulnerable populations in specific counties were identified, and information was shared with internal groups: public health preparedness, emergency management, communicable disease, and environmental health. Syndromic surveillance may also provide some assurance of the absence of health impacts in some situations. The potentially unique data sources and data elements collected by syndromic surveillance systems may also be used for evaluating disease (or adverse health outcomes) over time or in relation to an exposure(s).

There are several types of syndromic surveillance systems used by jurisdictions in the U.S.: Electronic Surveillance System for the Early Notification of Community-Based Epidemics (ESSENCE) within the National Syndromic Surveillance Program (NSSP)[1], local installations of ESSENCE, commercial syndromic surveillance systems such as EpiCenter, and in-house (e.g., created by the jurisdiction) syndromic surveillance systems [CDC 2017]. The majority of syndromic surveillance systems collect data from emergency departments (EDs), which is the focus of this document. Depending on the jurisdiction, syndromic surveillance systems may also include: ambulance or emergency transport dispatches, calls to poison centers, urgent care or ambulatory care center visits, in-patient hospitalizations, or school absenteeism.

In order to provide near real-time information, EDs typically provide preclinical information to the system. The preclinical information may include chief complaints, an admission diagnosis code, and, depending on the system and facility, triage notes and patient vitals (e.g., temperature or blood pressure) [CDC 2015]. Preclinical information is collected prior to physician evaluation and a diagnosis determination; whereas the data from traditional surveillance sources are provided after the clinical evaluation and/or lab testing, resulting in a more accurate diagnosis.

Case definitions can be designed using keywords (and/or diagnosis codes) to identify patients (e.g., from ED visits) with outcome symptoms that reflect the distribution of the confirmed designated health outcome. EDs may update individual visit data, providing discharge (i.e., post-visit) diagnosis codes (i.e., diagnosis or external cause codes). Analysis of discharge diagnostic codes in combination with preclinical

[1] The NSSP BioSense platform hosts ESSENCE along with a number of other software tools https://www.cdc.gov/nssp/biosense/index.html.

free-text data may also provide useful information such as the situation at the time of injury or disease onset. For instance, a patient with a diagnosis of carbon monoxide poisoning may indicate to the intake nurse that the exposure was related to a generator or related to exhaust fumes from a car. Additionally, analysis of both diagnosis codes and free-text information may provide a case definition validation, of sorts, via concordance of symptoms with diagnoses.

Using syndromic surveillance systems for climate and health surveillance offers the unique opportunity to help quantify and track in near-real time the burden of disease from climate and weather impacts. Once the disease burden for a climate-related health outcome is described, other climate and health public health initiatives can begin. Syndromic surveillance system administrators and epidemiologists may work together to develop syndromes for climate and health conditions, such as impacts from heat, cold, fire, or extreme weather events. **This guidance document will provide instruction in five areas: (1) identifying a weather- or climate-related surveillance outcome, (2) developing a syndrome case definition, (3) combining, externally and internally, syndromic surveillance data with environmental data, (4) interpretation and display of data, and (5) engaging with partners. The final section of the document will discuss the strengths and limitations of adding data from a syndromic surveillance system to climate and health surveillance.**

The climate and health surveillance workgroup hopes that this document may serve as a guide for public health professionals to understand and implement climate and health syndromic surveillance in their jurisdiction. All unreferenced state-specific examples presented in the document were provided by workgroup members.

HOW MIGHT SYNDROMIC SURVEILLANCE DATA SUPPLEMENT TRADITIONAL SURVEILLANCE METHODS OR SYSTEMS?

Syndromic surveillance data may be used for near real-time detection and monitoring of disease outbreaks and public health emergencies, monitoring of disease trends, case finding, seasonal event response, program management, and development of summary reports. Syndromic surveillance can enhance current surveillance by providing, in some cases, the most up-to-date information on the health impact of an event, and it can contribute to an appropriate and timely public health response. An additional notable characteristic of syndromic surveillance systems is the ability to monitor both communicable and non-communicable health outcomes that, depending on the system, may be entirely user-defined. In addition to health outcomes it may be possible to identify vulnerable populations, such as individuals with a specific occupation or who are homeless. Depending on the outcome, the potential flexibility in defining a syndromic surveillance outcome(s) may provide a more complete picture (e.g., situation) of the health impact of an event than traditional surveillance alone. It may additionally enhance traditional disease surveillance efforts if reportable diseases detected exclusively through syndromic surveillance queries are used by public health authorities as opportunities to educate healthcare providers regarding reporting requirements [O'Connell 2010].

II: IDENTIFYING A WEATHER- OR CLIMATE-RELATED OUTCOME FOR SURVEILLANCE

Climate change represents a significant threat to the health and wellbeing of individuals and, as the climate continues to change, the risk to human and animal health continues to grow [Frumkin 2008]. Rising greenhouse gas concentrations result in increases in temperature, changes in precipitation, increases in the frequency and intensity of some extreme weather events, and rising sea levels [Hess 2012]. Impacts of these factors endanger both human and animal health by affecting food and water sources, the air, weather experiences, and interactions with the built and natural environments [Hess 2012]. In the context of climate change, it is important to identify outcomes related to the adverse event or exposure. The following list includes general items to consider when developing an outcome for surveillance:

1. Identify/consider adverse outcomes directly related to current/forecasted weather patterns
2. Identify/consider adverse outcomes related to environmental exposures whose occurrence may change (e.g., increase) or shift geographically due to climate change
3. Note how, when, and where health impacts will vary by regions (or smaller geographies) and populations due to a susceptibility (e.g., vulnerable sub-populations or location in a flood plain), adaptability (e.g., availability of resources) and ability to respond to adverse events and exposures
4. Understand and account for potentially multiple adverse outcomes associated with a single event/exposure

Climate factors can affect health outcomes in various ways. Some effects are relatively direct such as extreme weather-related injury, illness, or death. Other effects have more complex pathways where the climate factor leads to an environmental change resulting in human health effects and disease [NIEHS 2016]. For example, higher temperatures and low precipitation can increase the number and severity of wildfires, which in turn can reduce air quality by releasing harmful emissions such as carbon monoxide and particulate matter. Higher summer temperatures are also associated with higher levels of ozone. The poor air quality leads to an increase in respiratory and cardiovascular illness such as asthma, bronchitis, chest pain and other ailments [Crimmins 2016]. Therefore, when deciding on an outcome for surveillance, it is important to think about how current or forecasted weather patterns may directly result in adverse health outcomes. It is also important to consider the adverse health outcomes related to other types of environmental exposures, such as wildfires or air pollution, that are impacted by changing climate patterns. **Table 1** below includes various examples of how climate factors can affect human health.

Table 1. Examples of climate change health impacts and related potential surveillance outcomes [Crimmins 2016].

Climate Indicator	Climate Driver	Exposure Pathway	Health Outcome
Extreme Heat	• More frequent elevated temperatures • Prolonged and more severe heat waves • Changes in timing and length or warm/cold seasons	• Exposure to elevated temperatures (daily, maximum, minimum and mean) • Exposure to elevated nightly temperatures • Combined impact of temperature, humidity, wind and sunlight	• Heat-related deaths, illness, hospital and emergency department visits
Air Quality	• Increasing atmospheric carbon dioxide • Increasing temperatures in many locations • Changes in precipitation patterns • Extreme weather events • Changes in cloudiness, humidity and wind speed	• Poor outdoor air quality due to high levels of ozone, particulate matter and carbon dioxide (CO_2) • Higher pollen counts with increased allergenicity, geographic range, a longer pollen season	• Premature death • Hospital ER visits for acute respiratory symptoms • Allergic sensitivity or disease • Lung cancer, chronic obstructive pulmonary disease (COPD), and cardiovascular disease associated with (particulate matter 2.5 micrometers ($PM_{2.5}$) exposure • Lost school or work days
Flooding	• More frequent and intense precipitation • More intense hurricane rainfall • Sea level rise-related increases in storm surge events	• Flood waters and debris • Loss of essential infrastructure • Contaminated drinking water • Evacuation and population displacement	• Drowning • Injuries • Mental health consequences • Gastrointestinal and other Illness
Vector-borne Diseases	• High and low temperature extremes • Changing precipitation patterns • Changes in season weather patterns	• Earlier and geographically expanded or shifted vector activity	• Vector-borne diseases such as, Lyme disease, Zika, Dengue and West Nile
Water-related Diseases	• Increasing sea surface temperature • Changes in precipitation, freshwater runoff, drought, sea-level rise, coastal flooding and storm surge, with resulting changes to coastal salinity, water	• Recreational exposure to seawater during swimming • Ingestion of raw or undercooked shellfish	• Diarrhea and intestinal illness • Wound infections • Eye and ear infections • Bloodstream infections • Death

Table 1. Examples of climate change health impacts and related potential surveillance outcomes [Crimmins 2016].

Climate Indicator	Climate Driver	Exposure Pathway	Health Outcome
	clarity or plankton abundance and composition		
Food Safety	• Temperature and extreme heat/cold • Humidity • Changes in the timing or length of season	• Increase growth of pathogens • Seasonal shifts in incidence cases related to pathogens • Consumption of under or improperly cooked foods (e.g., lack of cooking/reheating methods during a power outage) • Food spoilage due to weather-related power outages	• Food-borne illness such as Salmonella, Norovirus, and Listeria
Other Climate Change Associated Outcomes	• Increased temperature • Precipitation extremes • Extreme weather events • Sea level rise • Changing wind patterns	• Severity of extreme weather events (drought, flooding, sand storms, wildfires) • Damage to homes, livelihoods, communities, and population displacement • Changes in life cycle of vector-borne diseases • Level of exposure to all of the above	• Negative Impact on mental health (distress, grief, depression, PTSD and anxiety disorders) • Strain on social relationships • Substance abuse • Resilience and growth after traumatic experience

Any given type of weather-event or environmental exposure (e.g., wildfire) will likely have multiple potential adverse health outcomes. Some of these outcomes may be a direct result of the event or exposure while other outcomes may be the result of intermediary causes. For instance, a winter storm may result in at least three separate exposure pathways: cold temperature, snow and ice, and high winds (**Figure 1**). Exposure to cold temperatures may result directly in cold-related injuries such as frost-bite or hypothermia. Snow and ice may result in slips, trips, and falls; motor vehicle crashes; or transportation disruptions. Transportation disruptions can lead to disrupted access to care (e.g., healthcare facilities or pharmacies) and exacerbation of chronic conditions. Additional guidance on creating these complex pathways can be found in the Casual Pathways section of the CDC document Projecting Climate Related Disease Burden [Hess 2015] or Chapter 4 (Scoping) and Appendix C in the Health Impact Assessment Toolkit 3rd edition [HIP 2011]. Joffe and Mindell provide a more advanced look at complex causal process diagraming [Joffe 2006].

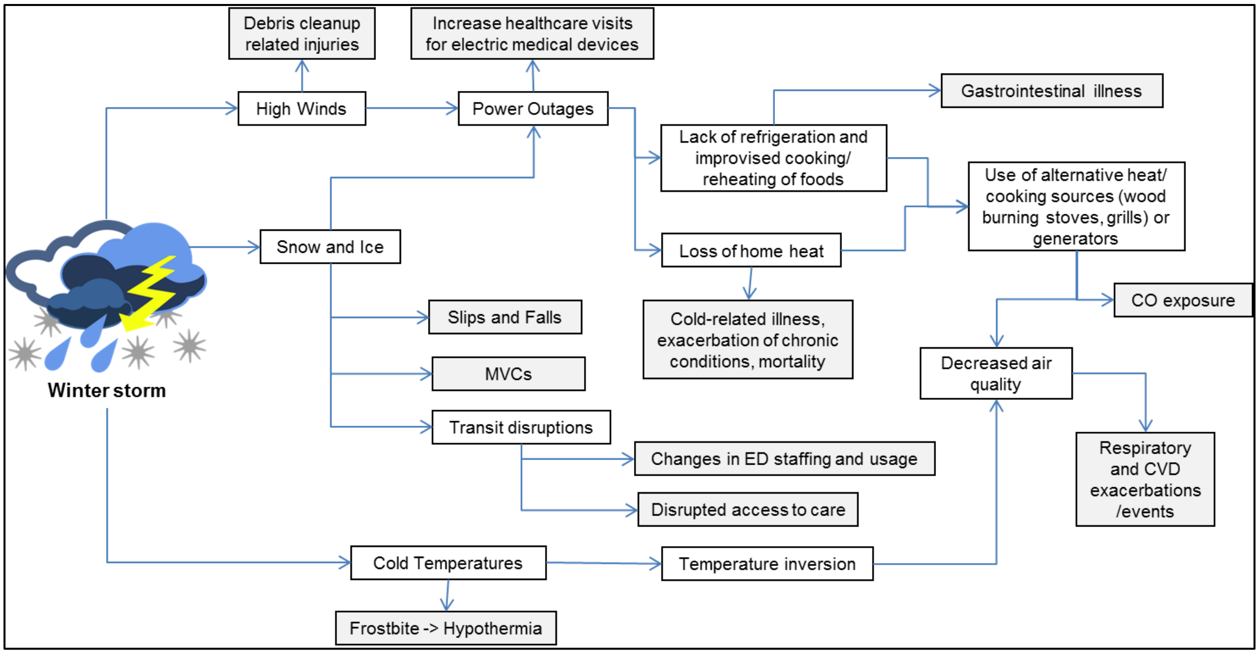

Figure 1. Potential direct and indirect effects of a winter storm. Example surveillance outcomes are highlighted in grey. Abbreviations: MVCs = motor vehicle crashes, ED = emergency department, CO = Carbon monoxide, CVD = cardiovascular disease

When deciding on health outcomes for surveillance, it is important to note that different regions and different populations in the country (or jurisdiction) will likely experience health impacts from climate change differently. In addition, some populations will be more vulnerable than others. Social determinants of health such as poverty, education, the use of non-English language, and other factors increase vulnerability to weather- or climate-related health outcomes [Manangan 2014]. Jurisdictions can use existing expertise and knowledge to choose the health outcome(s) with the largest projected impact and can potentially focus on vulnerable sub-populations. This may entail talking with or reviewing the work of other jurisdictions to inform which surveillance outcomes should be considered. It may be especially helpful to look at similar jurisdictions in a region as different climate factors affect different regions in the U.S. A summary of regional differences, including examples, can be found in the Regions section (chapters 16-25) of the 2014 National Climate Assessment located at: http://nca2014.globalchange.gov/report [Melillo 2014].

It is also possible that a surveillance outcome may be identified by information from another data source. For example, in 2006, the Maricopa County Department of Public Health (Arizona) observed an increase in heat-related deaths which initiated communication with the Office of Medical Examiner, resulting in development of ongoing heat-associated mortality surveillance [MC DPH 2016]. Maricopa County is currently using their heat-related surveillance model to initiate surveillance for other climate outcomes in order to monitor health outcomes related to dust storms, allergen levels, and wildfires.

Finally, when considering which surveillance outcomes to utilize, it is useful to assess the priorities and available resources of your jurisdiction. It is up to each jurisdiction to determine where the resources are best spent and to understand the jurisdiction's capacity to implement any program. How will the syndromic surveillance data be used? What types of solutions and interventions can be implemented based on the near real-time results? Can the syndromic surveillance data be used to contribute evidence to implement or direct the implementation of a solution to the outcome?

III: DEVELOPING A SYNDROME CASE DEFINITION

Once a surveillance outcome has been determined, a syndrome will need to be created to identify patients with that outcome or symptoms of that outcome. This section will discuss how to create a syndrome case definition and how to determine the effectiveness of the case definition in capturing patients with the particular surveillance outcome.[2] Before creating the case definition consider the data sources that are included in your syndromic surveillance system and if a patient with the selected outcome will be seen in that data source (e.g., seeking care at ED for a minor cold). The process of developing a case definition is iterative and the order of step completion is potentially non-linear. However, the process, in general, can be broken down as follows:

1. Decide the objective of the surveillance (e.g., broad definition or narrow definition)
2. Decide if the definition will be based on keywords, diagnosis codes, or both
3. Select the keywords and/or diagnosis codes
4. Validate and refine the selected keywords or diagnosis codes
5. Decide if the definition will be restricted by other factors (e.g., time period = summer months or only unintentional cases) and what those factors will be
6. Evaluate the effectiveness of the case definition

Because the terminology used by different syndromic surveillance systems may differ, for this document, the *case definition* refers to the particular keywords and diagnosis codes used to create the syndrome. The term *query* refers to how a syndrome case definition is implemented in a jurisdiction's syndromic surveillance system syntax (e.g., SQL or SAS).

Case definitions can either be broad or narrow. A narrow definition will have fewer false positives than a broader definition, but a broader definition will capture more cases. Depending on the use, it may not be necessary to capture most cases. A narrow definition that is representative of all cases resulting in the same conclusions that would have occurred if most cases were identified may be effective. A broader definition may be more useful for rare outcomes, small populations, or new and emerging diseases where the symptomology is not yet completely understood (e.g., Zika, novel flu, vector-borne disease shifting

[2] Note that guidelines for developing a heat-related illness case definition and query, including potential uses and methods of evaluation, has been published by the Council of State and Territorial Epidemiologist (CSTE) [CSTE 2016].

regions). When developing a case definition, it can be helpful to start with a broad definition, capturing as many probable cases as possible and then refine the definition to increase the specificity (i.e., proportion of cases without the outcome are not captured by the definition).

After the syndrome case definition has been finalized, alert thresholds will need to be determined. These thresholds may be based on the statistical algorithms used by your jurisdiction's syndromic surveillance system[3] to identify higher than expected number of syndrome cases (i.e., surveillance signals). Alternatively, it may be decided that all identified syndrome cases should be reviewed. The frequency of review will depend on the purpose of the surveillance.

> Insert 1: Hypothetical case definition development
>
> Scenario 1: Health Department X (HDX) is preparing for a hurricane. As part of the emergency planning and response, a carbon monoxide case definition is developed. The exposure of interest is carbon monoxide poisoning due to generator misuse. HDX plans to update their emergency operations center (EOC) daily. The case definition query will be run every day till the EOC stands down or all power is restored. Based on prior information from the death certificate and hospital discharge records, HDX believes there is a low prevalence of carbon monoxide cases in their state. They decide to develop a broad definition based on chief complaint keywords that will capture as many cases as possible. After a conversation with a neighboring state, HDX decides to use a similar case definition. During the response, HDX plans to manually review the chief complaints from identified case.
>
> Scenario 2: Health Department Z (HDZ) has decided to use their syndromic surveillance system for surveillance of heat-related illness due to outdoor ambient temperature. After reviewing the literature, HDZ understands that high outdoor ambient temperature may result in many different health outcomes such as cardiovascular or respiratory disease. HDZ decides to use the specific outcome of heat-related illness. They decide to use both keywords and diagnosis codes. HDZ starts out by using the CSTE heat query in ESSENCE. However, to make sure they haven't missed any keywords, HDZ extracts all records for the prior year with a diagnosis code of heat-related illness. They then examine the chief complaints and triage notes for any additional inclusion/exclusion keywords. After a final keyword definition was created, HDZ used the discharge diagnosis to calculate the sensitivity and positive predictive value. They also compared daily counts identified by the heat-related illness diagnosis and keyword case definition with daily counts of heat-related hospitalizations to determine if temporal pattern was similar.

KEYWORDS

Keywords are identified from preclinical administrative notes (e.g., chief complaints or triage notes) which are usually free text fields. However, some facilities use pre-defined chief complaint pick-lists (e.g., drop down menus). These administrative notes are typically recorded at time of the intake/admission and are based on the patient's complaint or the nurse's initial assessment of that patient at triage. These notes are available in near real-time – dependent on when the system is updated (e.g., hourly, every 12 hours, every 24 hours). For each record in the syndromic surveillance system, specific inclusion and exclusion keywords located in the administrative notes are used to identify cases with symptoms of a particular outcome or exposure. The inclusion keywords are used to identify potential

[3] Contact your syndromic surveillance coordinator to discuss the algorithms currently being used in the system.

cases. The exclusion keywords are used to remove cases that have an inclusion keyword but do not have the outcome symptoms. For instance, if the goal is to identify cases of carbon monoxide poisoning due to generators, then an exclusion keyword may be “fire.” Cases with carbon monoxide poisoning due to smoke inhalation would then be removed. Dependent on the jurisdiction, keywords may be in languages other than English (e.g., Demasiado caliente [English translation: too hot]) or may be abbreviations (e.g., OTJ = on the job). The process of identifying syndrome keywords is iterative and may include a combination of the methods discussed below. These methods were identified by the workgroup as common ways of identifying syndrome keywords. The use of the method(s) will depend on the resources available to the public health practitioner. Note that none of the methods are exact and there is a component of personal decision making.

<u>Identify keywords based on keywords used in another jurisdiction’s syndromic surveillance system</u>: This can be as simple as contacting a colleague from another jurisdiction and requesting their case definition. Depending on the syndrome, there may be guidance documents available with a summary of keywords. For instance, **Table 2** contains the carbon monoxide keyword definitions from multiple states. Heat-related illness syndrome keywords were published in a Council of State and Territorial Epidemiologist (CSTE) guidance document for heat-related syndromic surveillance [CSTE 2016]. A literature search may also provide articles with keywords used in prior studies.

<u>Identify keywords based on diagnosis codes</u>: This method requires your syndromic surveillance system to receive diagnosis codes. The system may contain one diagnosis text field with multiple diagnosis codes or multiple numeric diagnosis fields with a single diagnosis code per field. This method works well for outcomes with a clear diagnosis code. For instance, the diagnosis code for the toxic effects of carbon monoxide is ICD-10-CM T58 or ICD-9-CM 986. All records with the desired diagnosis codes (e.g., ICD-10-CM T58) are extracted into a dataset. The corresponding chief complaints and, if available, triage notes are read to identify keywords. This process can be done manually by reading each record and visually identifying the most common outcome-specific words. Or the data can be placed into a text mining program to identify common outcome-specific words. The threshold for a “common” word will be determined by the public health practitioner and the frequency of words (or phrases) within the data.

<u>Identify keywords based on an event</u>: This approach is retrospective. After a particular event has occurred, like a flood or a hurricane, all records during the event time period and the affected geographic area can be extracted into a dataset. Similar to the prior method, the chief complaints and triage notes are reviewed to identify the most common keywords.

<u>Identify keywords by speaking with partners</u>: Keywords may be identified by discussing syndrome case definition creation with knowledgeable partners, especially experts on the health outcome and community members and medical professionals who are familiar with the populations who most often develop these outcomes. Community members and stakeholders may be able to provide more detailed and granular information for defining keywords as well as timeliness of when to use the keywords (see Other Factors,

page 15), whereas experts on the outcome may help more with common diagnosis codes and where to look for important information within available data elements.

Identify keywords based on an activity: This approach attempts to capture visits where the injury or illness may be due to a climate-related or impacted activity. For instance, the New Jersey Department of Health created a case definition to identify injuries to tree workers (e.g., when clearing roadways or downed wires) in the aftermath of hurricanes [Borjan 2017b]. This method may require input from partners. Again, the chief complaints and triage notes are reviewed to identify the most common keywords. For this approach, it may be best to start with a very broad case definition. After reviewing visits captured by the broad case definition, the case definition can subsequently be narrowed by refining keywords or by the addition of exclusion terms. Addition of common misspellings of keywords to the case definition should be considered due to the nature of free text entry of chief complaints in many ED (e.g., including "CO2" in a carbon monoxide poisoning syndrome case definition).

Identify keywords by machine learning: The iterative process of refining the case definition can be automated. While this may be a more complicated method and is dependent on available expertise, it may provide a more accurate case definition and reduce the time allocation required for refining and updating the definition. A simple machine learning process is detailed in a later section of this document (Page 19). As a brief summary, the process starts by creating a data set of true positive and true negative cases (i.e., ED visits with and without the syndrome of interest) containing a column that identifies/labels them as such, followed by transforming the data set for analysis and development of a statistical model. The frequency of each word is identified and the public health practitioner can decide manually or via a statistical algorithm to include or exclude additional words.

DIAGNOSIS CODES

When determining whether to use diagnosis codes, there are a few things to keep in mind. Discharge (or final) diagnosis codes are assigned from physician notes and are recorded mainly for billing purposes. As the diagnosis codes are assigned at the end of the visit when all the information (e.g., laboratory test) is available, the codes may represent the actual condition as opposed to the symptoms of the condition. Therefore, the codes may have a higher sensitivity (identify true cases) than the keywords. However, for many systems, the discharge diagnosis is available only after an extended period of time. For instance, in North Carolina the majority of diagnosis codes for an ED visit are received between 48 hours and 2 weeks after the visit [Travers 2006]. Additionally, the accuracy of the codes may vary from system to system dependent on the quality of data received from the reporting facilities and how (if at all) data are updated. Receipt of diagnosis codes may also fluctuate over the year, potentially impacting any type of trend analysis or identification of unusual peaks (i.e., higher than expected cases). Before using the diagnosis codes as part of a case definition, the public health practitioner should discuss the quality of the diagnosis codes with their syndromic surveillance coordinators.

Table 2: Carbon Monoxide Syndrome definitions by state

	Essence	KY	NC	NJ	MI
Type	Chief complaints	Chief complaints	DX codes	Chief complaint/DX codes	
Inclusion Keyword	CARBON (10) COPOISONING (10) CO POISONING (10)	*CO exposure* *carbon* *monoxide* *CO poison*		toxic fume smoke inhal carbon mono carbon monoxide co exp	carbon monoxide expos CO2 oxide poisoning c02
Inclusion ICD-9-CM			986, E868.3, E868.8, E868.9, E982.1, E868.2, E982.0	986, E8689, E868.9, E8688, E868.8, E8683, E868.3, E8682, E9821, E982.1, E9820, E982.0, E868.2	
Inclusion ICD-10-CM			T58, T58.0, T58.01XA, T58.01XD, T58.04XA, T58.04XD, T58.1, T58.11XA, T58.11XD, T58.14XA, T58.14XD, T58.2, T58.2X, T58.2X1A, T58.2X1D, T58.2X4A, T58.2X4D, T58.8, T58.8X, T58.8X1A, T58.8X1D, T58.8X4A, T58.8X4D, T58.9, T58.91XA, T58.91XD, T58.94XA, T58.94XD		
Exclusion keywords and diagnosis codes				ICD-9-CM: E99, E97, E96, E95	std sti hiv bloo flui meth commu bat rsa scab syph emp occ pero radia croup strep work hydro mold bite needl pertus cold smok asbe acid tb eye drug mump food rat toxi rash chem pepp sharp dent powd menin sun rabi ivy fume eto shing whoo clea inf lead alco
Notes				For severe weather: additional inclusion keywords are EXHAUST GAS, EXHAUST; additional exclusion keywords are EXHAUSTED, EXHAUSTION; and diagnosis code is 508.2.	

Table 2 (cont.): Carbon Monoxide Syndrome definitions by state

	OR	KS	PA	VT
Type	Chief complaint/DX codes	Chief complaint/Triage notes/DX text/DX codes	Chief complaint	Chief complaint/ DX codes
Inclusion Keyword	^co pois^ ^c o pois^ ^co expos^ ^c o expos^ ^carbon mono^ ^co2 pois^ ^co 2 pois^ ^c o 2 pois^ ^co2 expos^ ^co 2 expos^ ^c o 2 expos^ ^carbon dio^ ^carbonoxi^	CARBON MONOXIDE CARBON MONOXIDE EVAL CARBON MONOXIDE EXPO CARBON MONOXIDE POISON MONOXIDE CO EXPO CO2 EXPO CO2 POIS CARB MONO TOX EFF CARB CARBN MONOX	('CO POI' or 'CO PIO') and not IVY CO INH CARBON MINOX MONOX MONIX DIOX DUE TO CO CO2 INHAL and CO EXP and CO and not 'PT CO'	'CO EXP' 'CO POI' 'CO PIO' 'CO POS' 'CO INH' EXPOS' AND ‘CO’ INHAL' and ‘CO’ POSSIBLE' AND ‘CO’ ‘DUE TO CO’ ‘CARBON’ ‘MONOXIDE’ ‘CO2’ ‘COPOISONING’ ‘CO INTOX’ ‘COINTOX’ ‘COEXP’ ‘COPOIS’ ‘CO ‘
Inclusion ICD-9-CM	^;986^	986, E9821, E982.1, V87.39, V8739		986
Inclusion ICD-10-CM	^;T58^			
Exclusion keywords and diagnosis codes	^suicid^ ^self^ ^psych^ ^fire^ ^smoke^ ^burn^	TOBACCO EXPOSURE ICD-9-CM: V4986, V49.86, 9986, 1986		
Notes	For wildfires, the keyword "house" is added to the exclusion terms and fire, smoke, burn are removed			Case definition still being evaluated. Anything containing “CO” and a space is manually evaluated.

The symbol for wildcard (^ or *) varies by syndromic surveillance system. For ESSENCE, a subtotal of ≥6 points are required for a visit to be captured.

Diagnosis codes may also be found in the administrative notes. Codes found in the administrative notes are assigned at time of intake/admission. As a result, diagnosis codes may also be treated as keywords. For instance, as part of Kansas' carbon monoxide case definition, ICD-9-CM code '986' (toxic effect of carbon monoxide) is searched for as an inclusion keyword in the admission notes while the ICD-9-CM codes '9986' (Persistent postoperative fistula) and '1986' (Secondary malignant neoplasm of other specified sites: Ovary) are treated as exclusion keywords.

Identify diagnosis codes based on previously published documents or another jurisdiction's case definition: Diagnosis codes are used for medical billing purposes and therefore are available in administrative datasets (e.g., hospital discharge data, ED visit data, Medicare/Medicaid data). As a result, diagnosis codes are used in many retrospective analyses and are the basis of numerous surveillance health indicators. Climate-related health surveillance indicators have been created by the Environmental Public Health Tracking Program (https://ephtracking.cdc.gov/searchMetadata) and CSTE (http://www.cste.org/group/indicators) to name a couple of examples. A simple literature search may identify peer-reviewed publications which could provide diagnosis codes for the chosen surveillance outcome (example reference = [Tsai 2016]). Additionally, as with keywords, requesting the case definition from another jurisdiction is also an option.

Identify diagnosis codes by searching the code manual: The ICD-10-CM (or ICD-9-CM) description for each code may be searched for the chosen outcome (e.g., carbon monoxide or Lyme disease). The code list and descriptions are provided by the Center for Disease Control (CDC) National Center for Health Statistics (ICD-10-CM: https://www.cdc.gov/nchs/icd/icd10cm.htm; ICD-9-CM: https://www.cdc.gov/nchs/icd/icd9cm.htm). Published code manuals may also contain an index with a list of diseases/outcomes and their corresponding codes ["ICD-10-CM" 2013]. However, when using this method, it is important to read the entire code description and make sure the code will identify cases with the particular outcome of interested (e.g., hyperthermia due to outdoor ambient temperatures [see **Insert 2**])

OTHER FACTORS

The selected outcome may encompass multiple etiologies and may require additional restrictions to the case definition. For instance, during the winter, cold-related surveillance may include unintentional, non-fire related carbon monoxide poisoning, while in the summer unintentional fire-related carbon monoxide poisoning may be part of wildfire surveillance. Depending on the restriction, inclusion or exclusion criteria may be created using either diagnosis codes, keywords, or both (**Table 2**). For instance, the public health practitioner may want to exclude all cases of carbon monoxide poisoning with a suicide or homicide diagnosis. Or the public health practitioner may want to include all cases of carbon monoxide poisoning with an unintentional or undetermined intent diagnosis. In the latter situation, cases without an intent diagnosis code would not be captured.

Insert 2: Relatedness Example - Hypothermia

It is always critical to be cognizant of the codes and keywords that you are using in a case definition, irrespective of your syndromic surveillance system. It is valuable to define your specific problem and to consult with subject matter experts.

During January 2017 Portland, Oregon experienced a prolonged and extreme winter storm. Multnomah County Health Department partners approached the Oregon ESSENCE team to inquire about monitoring hypothermia-related ED and urgent care visits. While there was an overarching concern about anyone exposed to the winter weather, a subpopulation of concern was individuals experiencing homelessness. ESSENCE did not have a pre-defined syndrome that was appropriate, so a new chief complaint and discharge diagnosis (CC/DD) query was drafted for cold exposure.

In the initial draft of the case definition, two ICD-10-CM codes were included that were later removed: T88.51 (hypothermia following anesthesia) and W93 (exposure to excessive cold of man-made origin). While both relate to "cold" or "hypothermia," neither were actually related to the problem of monitoring increases in outside, weather-related hypothermia visits. The final case definition used included the following codes and terms: T68 (hypothermia), X31 (exposure to excessive natural cold), T33 (superficial frostbite), T34 (frostbite with tissue necrosis), "cold exposure," "hypothermia," or "frost bit." [Personal communication: Amy Zlot, Multnomah County Health Department, Oregon, April 2017]

The developed case definition may be used all of the time, during an event, or may vary by season. As in the example above, you may choose to include non-fire related carbon monoxide keywords in the winter and fire-related keywords in the summer. Altering the case definition by season provides better data integrity and may help with lowering the counts of false positives in your dataset. Some groups may choose to utilize the same case definition year-round as part of syndromic surveillance, or only use the case definition during certain annual events or time periods as part of enhanced syndromic surveillance (e.g., using the case definition for enhanced surveillance of carbon monoxide poisoning after a hurricane or enhancing mosquito-borne surveillance via case identification [see **Insert 3**]).

Finally, in areas with a small population, a spike (or greater than expected cases) may not be observed for a particular outcome due to natural statistical variability. Review of all cases with the identified outcome of concern may be appropriate. Or a case definition based only on the total number of cases (e.g., all ED visits) for a specific vulnerable demographic group may be used. For instance, during a wildfire event in a rural area, statistically significant increases in county-specific visits for asthma may not be observed but increased cases of total ED visits for elementary school aged children may be observed. Additionally, when an increase is observed for case definitions comprised of all visits within a specific vulnerable population group, the public health professional may be able to backtrack to a particular event, such as a wildfire, and then examine outcome specific cases.

Insert 3: Enhanced surveillance example – Mosquito-borne disease surveillance

The changing climate has affected the geographical distribution and life cycle of vector-borne diseases [Luber 2014; Beard 2016]. The magnitude of the geographical shift in U.S. regions is unclear as the shift is based on many factors of which climate change is but one. However, it is suspected that non-endemic diseases may become endemic as mosquito species populate new areas [Beard 2016]. In Arizona, syndromic surveillance is being used to enhance routine arbovirus surveillance. Surveillance occurs for both endemic (West Nile and St. Louis Encephalitis) and travel associated (Dengue, Chikungunya, and Zika) mosquito-borne diseases. Routine surveillance identifies cases reported by providers and laboratories, in accordance with Arizona Administrative Code. In order to capture potentially missed cases or to identify cases sooner, the Arizona Department of Health Services (ADHS) has implemented several enhanced surveillance strategies, including notification from commercial labs at the time of the order (rather than result) and syndromic surveillance. ADHS has defined case definitions in the National Syndromic Surveillance Program's version of ESSENCE (syndromic surveillance system) to identify any visits with a chief complaint or diagnosis any of the five mosquito-borne diseases listed above. The query is monitored twice a week during the peak arboviral season and once a week during the off-season. ADHS notifies the local public health jurisdiction when potential new cases are identified. The local health department will determine if the case requires follow-up (e.g., "traveled to Mexico – presenting with dengue" versus "history of west nile") or if the case has already been identified via other surveillance mechanisms. If follow-up is necessary, the local health department can use the patient medical record number to obtain the required information from the reporting facility. All mosquito-borne disease cases identified in Arizona, regardless of identification method, are summarized and shared with Arizona's public health and vector partners across the state. In this example, data from the syndromic surveillance system does not trigger action but instead provides a potentially more complete picture of the disease burden in Arizona. [Personal communication: Arizona Department of Health Services, May 2017]

VALIDATE AND EVALUATE EFFECTIVENESS OF CASE DEFINITION

Components of the syndrome case definition may be evaluated during or after the development process to assist in refining the definition. After the syndrome case definition has been completed, the effectiveness of the definition should to be assessed to determine if: 1) the definition identifies cases with the surveillance outcome and 2) the syndrome will add to the current weather-related surveillance, that is, the pattern of identified cases is associated with the weather-related exposure or event. This latter determination refers to the use of syndromic surveillance for situational awareness, tracking trends over time (either short- or long-term), and retrospective analysis. In other words, will the syndrome provide information that can be used for situational awareness during an event?

MANUAL REVIEW

The simplest method for evaluating the accuracy of the case definition (or individual components) is to review the chief complaint or triage notes associated with each identified case. For example, does the keyword phrase "to hot" pull potential heat-related cases or cases where the individual had a dental sensitivity, "to hot liquid"? [CSTE 2016]. This evaluation can be done by manually reviewing all or a random sample of cases within a particular time frame. Manual review may also be conducted on potentially false positive cases – cases identified by the syndrome but may not have the outcome of interest. Potentially false positive cases may be identified by keywords or diagnosis codes. Finally, calculating the number of visits identified by each keyword or diagnosis code will help determine which inclusion or exclusion keywords are important (or not necessary) to include in the case definition.

IDENTIFYING A GOLD STANDARD AND CALCULATING PERFORMANCE MEASURES

A "gold standard" may be used to identify true positives – cases or visits that *truly* have the surveillance outcome. Since the discharge diagnosis code(s) are assigned after the visit, they may be used as a "gold standard" when evaluating the keyword part of the case definition, which is recorded at the beginning of the visit. Therefore, a true positive would be defined as a case with both a diagnosis code and a syndrome keyword identifying the outcome. However, if diagnosis codes are unavailable within the syndromic surveillance system, diagnosis codes may be obtained by linking the case(s) identified by the syndrome case definition to the corresponding visit in the ED discharge or hospital discharge data. Additionally, a "gold standard" may be identified using other methods or data sources, such as a review of patient medical charts.

By applying the "gold standard," positive predictive value may be calculated to determine the accuracy of the definition. The positive predictive value (PPV) represents the proportion of cases identified by a syndrome keyword(s) that also had a diagnosis code (i.e., among those visits captured by the keyword, how many are true cases). Note that the PPV will be higher for case definitions with clear symptoms (or keywords) related to the diagnosis [CSTE 2016]. For instance, if the keyword pulled from the chief complaint is *carbon monoxide* or *CO exposure* (a narrow definition) it is highly likely that the official diagnosis will be carbon monoxide poisoning. The PPV may also be higher during an active event [CSTE 2016]. For example, the PPV of a New Jersey heat syndrome case definition improved from 40% to 59% when restricted to a major heat wave [Berry 2013]. Finally, the PPV may also vary due to the frequency of the surveillance outcome in the population [CSTE 2016].

The sensitivity and specificity also may be calculated to validate the keyword part of the definition. The sensitivity represents the proportion of cases with a diagnosis code for the specified outcome that were identified by syndrome keywords (i.e., among those with the outcome, how well do the keyword(s) work to capture the cases). The specificity represents the proportion of, for instance, ED visits that do not have the outcome and were not classified as a case by the syndrome (i.e., how well do the keywords correctly exclude cases without the outcome of interest).

Temporality comparison and weather assessment

Ideally, conclusions and actions based on near real-time results of the syndromic surveillance system should be the same (or similar) to the conclusions that would have been made using results from confirmed case data which may not be available in a timely manner. If the two distributions (i.e., syndrome cases and confirmed cases) are similar, then even if the sensitivity and PPV are low, the syndrome will still be useful. The daily counts of cases identified by the syndrome case definition can be compared to daily counts of confirmed cases, such as cases identified by diagnosis codes in an administrative data source (e.g., ED visits or hospital discharge data). The comparison can be done visually through graphical displays (time-series plots or scatterplots) or through statistical comparison using, for instance, correlation or times-series analysis [Mathes 2011; Berry 2013; Tsai 2016]. The relationship between syndromic cases and meteorological/event data may also be compared to the relationship confirmed cases and meteorological/event data.

Finally, the syndrome case definition may under- or over-estimate cases. An examination of the selected outcome in other sources of data, such as the ED discharge or hospital discharge data or vital statistics, should be reviewed after an event or surveillance time period (e.g., summer). The examination will help to quantify the limitations of the syndromic surveillance system and potentially understand how the identified syndromic cases fit into the overall surveillance of the outcome.

USING MACHINE LEARNING TECHNIQUES TO IDENTIFY KEYWORDS

The accuracy of a syndrome case definition will vary over time and over space. For example, keywords that are common in Arizona may be very rare in North Dakota. In addition, new words are introduced every day in the body of the chief complaints and triage notes of the ED electronic records. Therefore, for each established case definition there is a need to regularly assess its accuracy and make adjustments to the query statement, especially to the underlying keywords. Checking a case definition’s accuracy may not be an easy task given the sheer size of the data involved. Fortunately, the task can be automated by using machine learning (ML) techniques. The following is a simple example of supervised machine learning and how this technique can be used to identify keywords that are associated with a syndrome. For more details on the process, including other techniques, refer to the following book: “Machine Learning with R”, 2nd Edition [Lantz 2015].

Step 1. Create a learning data set: From the output of an existing query on a recent batch of ED data select the true positive cases, and create a new data set. For example, for carbon monoxide surveillance only include true carbon monoxide cases. If not certain about a record, do not include it. Merge the following fields into one text field: Chief complaint, Triage notes, Diagnosis text, and Diagnosis codes. Preferably include 100 records or more in this ‘learning’ data set. Assign or use a unique identifier for each record. Subset the data by keeping two fields: the Unique ID field and the merged text field.

Step 2. Create a corpus out of the learning data set: Transform the dataset created in step 1 into a corpus. A corpus is a collection of text documents specifically designed for text processing during certain machine learning applications. In this situation, each document of the corpus represents a record from the learning data set. In R, the text mining package tm can be used to create[4] a corpus [Feinerer 2008].

Step 3. Prepare the corpus for analysis: In order to perform any analysis on the words found in the corpus, the text needs to be standardized. To do that, punctuations, other non-letter characters, and numbers, if diagnosis codes are not included, need to be removed from the documents. Since this process is case sensitive, the whole corpus should be converted to lower or upper case to allow for an accurate count of words. Next, words may need to be truncated or stemmed to allow for the groupings. Stemming refers to the process of reducing inflected or sometimes derived words to their work stem, base or root form. Verb tenses and singular and plural nouns are some examples of words that may need to be stemmed to facilitate grouping. For example, the stem for accident, accidental, and accidents may be "accid". By stemming the words in a corpus, one can group several variants of a particular word more efficiently and thus calculate more accurately the frequency of the word in the corpus. Finally, "stop words" (i.e., high frequency words that do not add information, such as: the, to, from, and, but, and, etc.), numbers, and words that are ubiquitous in the corpus (e.g., patient, sick, or pain) are usually removed to allow more meaningful ones to surface. To perform this step well requires a solid knowledge of the data. It will take many trials and errors to get this step right, even for experienced users.

Step 4. Split each text document into separate words or groupings: In this step, the standardized text document will be split into words or strings of words according to a process called tokenization. Tokenization is very useful in providing context to words or tokens. A token is a sequence of characters or words that are grouped together for processing [Manning 2008]. For example, in this sentence: "Patient denied loss of consciousness". The word "denied" is most likely going to produce a false positive case. However, by tokenizing the sentence (chopping it into words) and creating n-grams (grouping words in a sequence of 1, 2, 3 words) it becomes less likely for this sentence to cause a false positive retrieval. In this context, n-grams are basically a sequence of tokens, where n indicates the number of tokens. Possible n-grams from the example sentence are (note that during the data preparation the stop word "of" was removed):

- 1 token or unigram: [patient] [denied] [loss] [consciousness] = 4 unigrams
- 2 tokens or bigram: [patient denied] [denied loss] [loss consciousness] = 3 bigrams
- 3 tokens or trigram [patient denied loss] [denied loss consciousness] 2 trigrams

[4] There are several other packages dedicated to text mining, including the caret package in R. Among the other open source languages, Python is another open source language which offers libraries for text mining and machine learning (e.g., scikit-learn). Additionally, commercial software such as SAS can be used to complete all the machine learning steps described in this section. An internet search on "text mining", "text analysis", "natural language processing" will provide other resources.

N-grams are often more efficient than very complex data mining methods. There are many ways to tokenize texts[5] but all lead to a structure commonly called document term matrix (DTM). When visualized a DTM looks like a table where, in this case, each row represents a visit record and each column is a word in the corpus. The value in each cell represents then the frequency of a word in a particular document or record (**Table 3**).

Table 3. Example of truncated document text matrix (DTM)

Unique ID	breath	dizzy	found	exposur	poison	monoxid
Rec00067	0	0	0	0	0	0
Rec00068	0	0	0	0	1	2
Rec00069	1	1	0	0	0	0
Rec00011	0	0	0	0	0	0
Rec00099	0	0	1	0	0	0

<u>Step 5. Inspect the text document matrix and select the new words</u>: Using the DTM, calculate the number of occurrences for each word in the corpus and create a list of words in descending order of frequency (**Table 4**).

Table 4. Example of ordered list of word frequencies in a carbon monoxide poisoning corpus

Word	carbon	monoxid	burn	Short	poison	accident	car	suicid	tube
Frequency order	*154*	*141*	*127*	*83*	*78*	*70*	*62*	*62*	*61*
Word	headach	home	attempt	exposur	co2	nausea	nbr	garag	famili
Frequency order	*56*	*56*	*52*	*52*	*50*	*45*	*43*	*40*	*30*

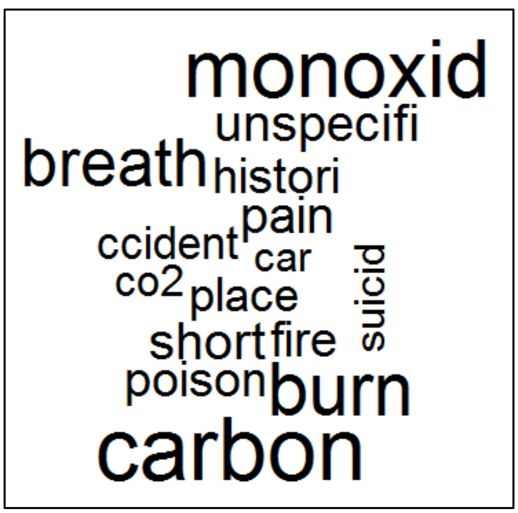

Figure 2. Example of word cloud for a carbon monoxide poisoning corpus

This list very frequently will contain words that were not included in the original case definition. The list can help decide if new words need to be included or old words need to be excluded. As part of the inspection of the DTM a word cloud can be created to visually detect the most important words.

In summary, the process described above is one of the simplest machine learning techniques that can be used to systematically discover new and important keywords that can be incorporated into syndrome classifications to increase the sensitivity and specificity of a syndrome case definition. Of course, machine learning can offer much more than finding keywords. It can be used to replace the query approach altogether by developing a statistical model and applying it to the data to predict the diagnosis or syndrome group for each record. If

[5] The R packages tm and NLP contain functions that help with tokenization and 'n-gramming'.

implemented correctly, machine learning, compared to query strategy, is faster, more accurate, and more scalable. However, it requires a higher level of analytic skills and typically more computing resources.

SYNDROMIC SURVEILLANCE OF WORK-RELATED OUTCOMES

According to CDC, workers may be vulnerable to increased injuries, illness, and death due to climate change and in industries associated with climate adaptation and mitigation efforts (e.g., green jobs/green technology) [CDC 2009; WHO 2014; Schulte 2016]. Extreme climate conditions can exacerbate existing health issues and cause previously unknown or unanticipated hazards [Schulte 2016; NIOSH 2016]. For example, outdoor workers, including oil field and utility workers may have increased exposure to ticks carrying Lyme disease [Schulte 2016]. Increases in respiratory or gastrointestinal outcomes have been documented for workers in composting facilities [Hambach 2012]. Injuries and illnesses have also been documented in rescue and clean-up workers after a hurricane or natural disaster [CDC 2005; Fayard 2009]. Syndromic surveillance can be used to capture work-related injuries due to climate events through the development of both work-related and weather-related case definitions.

A work-related injury and illness case definition needs to be developed. The definition may be used alone or in combination with another case definition (e.g., carbon monoxide poisoning). The development and validation of a work-related case definition follows the processes outlined in the first three parts of Section III (see pages 9-15). A collection of keywords and phrases specific to work-related injuries and illnesses are developed by assessing the free text chief complaint field and triage notes (i.e., preclinical admission notes), and ICD-10-CM (or ICD-9-CM) codes found in the record for each ED visit to capture the full range of non-fatal work-related injuries reported to the syndromic surveillance system. Potential keywords and diagnosis codes are listed in **Table 5**. Depending on the syndromic surveillance system, worker's compensation as expected payer may also be included in the definition. Once an initial case definition is developed, the definition is refined using keywords or ICD codes from historic data.

The use of ED discharge or hospital discharge data obtained from all acute care general hospitals through electronic reporting of Uniform Billing (UB) records can be used to help validate the selected keywords. These data provide standard variables on patient identifiers, diagnosis (i.e., ICD-9/10-CM codes), nature of injury, external cause (e.g., ICD-9-CM E-codes), place of occurrence, and payment information. The use of the codes for *Supplementary Classification of Factors Influencing Health Status and Contact with Health Services* (ICD-9-CM V-codes, ICD-10-CM Z-codes) and workers' compensation as a primary (expected) payer allows for obtaining injuries that occurred specifically in the workplace. However, this may undercount work-related injuries. These data enable the identification of work-related injuries that are severe enough to require hospitalization or an ED visit.

The work-related case definition will need to be evaluated to determine if work-related cases (e.g., ED visits) are being identified. Sensitivity, specificity, and positive predictive value (PPV) can be calculated for the list of work-related keywords identified through initial methods. Cases are considered "true positives" if keywords matched the identified gold standard, for instance ICD-9-CM E-codes. If cases did not have keywords that matched the ICD-9-CM E-codes they are considered to be "false positives" [Borjan 2017]. Once the syndrome case definition is developed and validated, preliminary alert thresholds for work-related injury events need to be determined. These alert thresholds may be based on absolute number of ED visits meeting the newly developed occupational syndromes or based on the number of visits needed for Occupational Safety and Health Administration (OSHA) or other agency response. Alerts received should be investigated immediately to determine if it is occupationally-related by contacting the facility (e.g., ED). Additionally, dependent on the outcome, the number of identified visits may be few enough that each work-related case may be investigated.

Table 5: Example keywords for work-related classifier by state

State	Essence (≥6 points)	NJ	NC	OR	Maricopa County, AZ
Type	Chief complaints	Chief complaints	Chief complaints/Triage notes	Chief complaints	Chief complaints
Inclusion Keyword	JOB (12) WORK (10) WORKER (10) WORKPLACE (10) WHILE WORKING (10) EMPLOYEE (8) COWORKER (10)	JOB AT WORK @WORK @ WORK WORK RELATED OCCUPA ACCIDENT WORK WORKPLACE WHILE WORK WORK-RELATED WORK INJ WORK ACC WORK WOUND WORKERS COMP WORKER'S COMP WORK MANS COMP WORKMENS COMP WORK COMP WORKMANS COMP WORKMENS COMPENSATION	at job at her job at his job at work Atwork at~wrk at her job at his work works at workman complaint worker complaint	*JOB* OTJ OJI *AT WORK* *WORK RELATED INJURY* CIVILIAN ACTIVITY DONE FI	Work "air force" or "bus driver" or construction or contractor or fire + fight, or landscap or "life guard" or lifeguard or mechanic, or military, or "postal service" or supervisor
Exclusion Keyword	WORK UP (-10) LAB WORK (-10) BLOOD WORK (-10) WORK OF BREATHING (-10) WORK BREATHING (-10) FIRE WORK (-10) DENTAL WORK (-10) DRUG (-4) SOCIAL WORKER (-10) SOCIAL WORK (-10)	WORKOUT WORK UP WORK NOTE LABWORK LAB WORK BLOODWORK BLOOD WORK		*CLEARANCE* *RETURN TO WORK* *NOTE*	("A/C" or "AC" or "air condit" or "swamp cooler" or "swap cooler") and "<> work"
Notes			Restricted to ≥ age 16 years or older. Includes expected payer = WC or ICD-9-CM: E900.0/ E900.1 or ICD-10-CM: Y99.0/Y99.1		Keywords only for cases previously categorized as heat-related illness syndrome

The symbol for wildcard (^ or *) varies by syndromic surveillance system. For ESSENCE, a subtotal of ≥6 points are required for a visit to be captured.

IV: USING ENVIRONMENTAL DATA WITH SYNDROMIC SURVEILLANCE

Just as public behavior (e.g., over-the-counter drug sales, complaints to utilities, or school and work absenteeism) can be early indicators of disease, environmental data are critical for risk assessment and are a valuable “pre-clinical” sources of information for syndromic surveillance [Berger 2006; May 2009]. The specific data will vary based on health outcomes of interest, local availability, and technical ability to incorporate data feeds into syndromic surveillance systems. Environmental data that could be used to improve situational awareness include but are not limited to: traditional meteorological observations like temperature and precipitation [Leonardi 2006; Josseran 2010; Perry 2011]; daily aeroallergen counts; monitored air quality observations or AQ index values; drinking water turbidity [Berger 2006]; satellite data showing vegetative greening or smoke plume optical depth [Rappold 2011; Tinling 2016; Merkord 2017]; National Weather Service (NWS) alerts, watches, and warnings; multi-month drought indexes; or indexes measuring larger scale phenomena like the El Niño Southern Oscillation (ENSO). While some data sources would provide general context, such as knowing that there is a storm warning for a specific part of your jurisdiction, to be most useful, the statistical associations between these indicators and health outcomes of interest need to be well-understood. Prior to implementing syndromic surveillance, it may be necessary to review existing health studies and/or to conduct a retrospective analysis of the relationship between weather metrics and the health outcome.

Practically speaking, using environmental data with syndromic surveillance health data will likely require the following steps:

1. Identify goal and potential uses of surveillance.
2. Identify the types of data (i.e., variables, time frame, geography) that are appropriate for your project based on literature, prior work, or consultation with a subject matter expert.
3. Identify a source for those data (i.e., data steward and actual data source, like an FTP site or web service).
4. Ask permission to use data, if applicable.
5. Temporally (e.g., daily, weekly, or event specific) and geographically (e.g., zip code, county, state) match the environmental data with the syndromic surveillance health data.
6. Maintain a working relationship with environmental data steward.
7. Demonstrate use.

The steps above are appropriate for using externally-housed data. If you are integrating environmental data into an existing syndromic surveillance system, there are additional steps which would occur between steps 5 and 6 listed above:

1. Work with IT staff or syndromic surveillance coordinator to add environmental data as a new data source in the system.

2. Validate environmental data within the syndromic surveillance system (i.e., is the data being incorporated properly).

EXTERNALLY-HOUSED DATA

Much of the work analyzing associations between syndromic surveillance data and environmental indicators has been done retrospectively. In response to extreme heat events, several syndromic surveillance systems have been evaluated for their ability to serve as heat health warning systems[6]. In England, as temperatures increased, calls to NHS Direct—a 24/7 nurse helpline—increased moderately overall and acutely for heat or sun stroke [Leonardi 2006]. Increased temperatures were also correlated with increased ED visits for diagnoses related to hyperthermia, malaise, dehydration, and hyponatremia in France [Josseran 2010]. And in Ontario, Canada, several weather predictors (i.e., temperature, humidity, and wind speed) were used in a retrospective study of heat-related illness ED visits [Perry 2011]. Syndromic surveillance data have also been used in retrospectively assessing cardiovascular-related ED visits associated with peat bog wildfire smoke exposure in North Carolina, using both satellite-measured aerosol optical depth to identify smoke-exposed counties [Rappold 2011] and county-level modeled particulate matter (PM) 2.5 [Tinling 2016].

Externally-housed environmental data, and knowledge of environmental event occurrences, have been used to inform heightened, real-time monitoring of health effects. During wildfires in San Diego County, CA in 2007, ED visits were monitored using BioSense [CDC 2008]. Syndromes of interest included respiratory disease, gastrointestinal disease, burns, and cardiac complaints. Increased visits were seen for respiratory disease, and additional analysis was done after the event to quantify the magnitude [CDC 2008]. Real-time monitoring was also done in the UK to assess health impacts related to a volcanic ash plume in 2010, but no increases in general practitioner consultations for syndromes of interest were observed [Elliot 2010].

INTEGRATING ENVIRONMENTAL DATA INTO SYNDROMIC SURVEILLANCE SYSTEMS

There are circumstances where having both health and environmental data in the same syndromic surveillance system have demonstrated utility, including heat-related illness and vector-borne diseases. There may be trade-offs in terms of timeliness and geographic scope, however. For example, weekly epidemiological data are paired with freely available “remotely-sensed environmental data,” (i.e., rainfall, temperature, vegetation greening, and surface moisture), in a unified database called EPIDEMIA to forecast malaria risk in Ethiopia [Merkord 2017]. Mosquito count data have been combined with climate-related indicators (i.e., tide height, rainfall, and sea surface temperature) to predict Ross River Virus

[6] Extreme heat is likely the most studied climate-related hazard. Temperature, and to a lesser extent humidity, are easily accessible weather variables, and some heat-related health effects, such as heat-related illness or all-cause mortality, are relatively easy to understand from a physiological perspective and have strong statistical associations with temperature and extreme heat events.

epidemics in Australia [Woodruff 2006]. In a World Health Organization review, climate plays a moderate or significant role in vector-borne diseases outbreaks like malaria, dengue, and St. Louis encephalitis; diarrheal disease outbreaks including cholera; and meningococcal meningitis outbreaks. The climate-epidemic relationships have been well quantified for these outcomes [Kuhn 2004].

Best practices for incorporating environmental data directly into syndromic surveillance systems used in the U.S. are still being developed. However, National Weather Service station data have been incorporated in the National Syndromic Surveillance Program (NSSP) version of ESSENCE, as well as several local installations. New York City (NYC) routinely incorporates temperature and heat index data into syndromic surveillance for heat-related ED visits and EMS calls during extreme heat events [Lane 2015]. The Oregon Health Authority and the Florida Department of Health are currently exploring the utility of having monitored air quality data directly accessible within their ESSENCE systems.

Insert 4: Integrating weather data into North Carolina's syndromic surveillance system

In 2016, North Carolina (NC) incorporated temperature and heat index (HI) data at the county level into their stand-alone syndromic surveillance system, NC DETECT. This project was done in collaboration between NC DETECT, NC Division of Public Health, and the State Climate Office of NC (SCONC). Temperature and humidity data are collected hourly from weather stations across NC and are uploaded daily into a databased maintained by SCONC. However, stations are not evenly distributed across the state, with some counties having multiple stations and other counties having no stations. Further, weather data quality and availability vary by station type. SCONC provided advice on which type of stations had the best data quality.

A correlation analysis between all weather stations was conducted to determine the degree of similarity between the station-specific exposure metrics and to assist in the selection of a single weather station for each county. Prior to analysis, the raw station-specific temperature and HI data for 1/1/2008–09/20/2015, provided by SCONC, were de-trended and the seasonal cycle removed. Initially, a station was chosen to represent a county based on station type. Using the correlation analysis results, if the chosen station was a poor representation of the county then a different station was chosen. For counties without a station, the correlation analysis results informed the choice of a substitute station from a bordering county within the same climate zone. The result was 71 stations which would provide daily weather data for 100 counties.

An account was provided by SCONC for NC DETECT to access hourly data via their web-service. The web-service was stress-tested to determine the amount of data that could be pulled at one time. The results of the stress-test indicated that hourly temperature and humidity data for all 71 stations for the past month could be extracted daily.

Using a perl script, the prior 30 days of data are downloaded daily from SCONC web-service in a flat file and uploaded into the NC DETECT database. Only data values not already included in the database are uploaded. In this manner, delayed submission of station data to SCONC due to malfunction errors are eventually incorporated into NC DETECT. The data are cleaned (e.g., deletion of implausible values), converted from Celsius to Fahrenheit, hourly HI and wind chill are calculated, daily max/min values are calculated, and the data are linked to its respective county. Temperature and HI values are presented alongside health data in NC DETECT's web-portal via charts and tables. [Harduar Morano 2016]

THE FUTURE OF ENVIRONMENTAL DATA ENHANCING SYNDROMIC SURVEILLANCE SYSTEMS

There are several challenges to using environmental data as part of syndromic surveillance. Getting data at similar geographic and temporal scales is a persistent challenge in public health [Kintziger 2017], not one limited to climate and health or syndromic surveillance work. However, care should be taken to consider how station-based data are aggregated (or not) within a system. Similarly, environmental information that is multi-day (e.g., storm watch) to seasonal (e.g., drought index or ENSO indicator) should be handled carefully. Before implementing surveillance enhanced with weather metrics, the relationship between the outcome and the weather variables should be examined. This will also help to inform display.

The algorithms used to assess increases in events (assumed to be health-related outcomes) are not necessarily appropriate for most environmental data. While an in-depth discussion of algorithms is beyond the scope of this guidance document, these limitations are known caveats of many systems, including ESSENCE. In the ESSENCE system, the default algorithm is Poisson/Regression/EWMA (exponentially weighted moving average). This algorithm analyzes the last 30 days, minus the last two days (to account for day-of-week or other anomalies), to determine if there were more than the expected number of events [Howard 2008]. For a weather variable like temperature, several years of data may be needed to assess trends. In NYC, counts of heat-related illness are included in statistical models that include several years of data and control for both time trends (such as day of week, month and year) and meteorological variables [Lane 2015]. This may help users assess whether counts are higher than expected for the time of year and weather conditions. It may be important to assess variations in temperature. For example, looking at the difference between the current day's temperature compared to the previous days', and/or assessing whether the temperature is significantly higher than average for the day or month (e.g., above the 90th percentile). Additionally, all algorithms in ESSENCE are one-sided, meaning they look for increases and not decreases in events. While this is usually appropriate for health data, there are numerous examples where you would want to know if an environmental indicator was lower than normal (e.g., minimum temperatures or rainfall). There are methods for assessing multiple data feeds simultaneously using "spatial and temporal data aggregation strategies," as explored using multiple clinical data sources [Burkom 2004]. However, assessing multiple data feeds that include one or more environmental indicator in near-real time is a largely unexplored challenge for syndromic surveillance system developers.

V: INTERPRETING AND DISPLAYING THE DATA

Climate-related case definitions can be applied to the entire state (or jurisdiction) or may be applied to a lower geographical area such as a county or a zip code. Applying the case definition to a smaller geographical area may be especially appropriate when only certain areas of a jurisdiction are affected.

For instance, during the response to hurricane Matthew in 2016 Georgia Department of Public Health reviewed syndrome query results in the four public health districts impacted by hurricane landfall [Borroto 2017].

Surveillance data are best presented and used in aggregate form unless individual cases are being verified (e.g., active follow-up with facility), additional situation information is being extracted, or case definitions are being revised. Data from the syndromic surveillance system may be presented in tabular form, using graphs or bar charts, or maps. This data may be stratified by demographic group, such as sex or age group (**Figure 3**). Data display may be available internally as part of the syndromic surveillance system. For instance, ESSENCE as part of the NSSP allows line graphs of cases with temperature (**Figure 4**) or maps by at the zip code level [CDC 2016]. In another example, Oregon's syndromic surveillance system displays near real-time data graphically in dashboards that are accessible by authorized users such as county health officials **(Figure 5**).

Data may also be summarized externally. External summarization and presentation of data may provide more flexibility in how the data are displayed and how the data are shared. This may include additional tables/figures or incorporation of data in weekly or monthly reports (see **Appendix A**). When creating external summarization reports, be sure to consider your audience. For instance, when partnering with a particular entity small numbers may be shared and line listings (i.e., detailed information for each case) may be presented, depending on the data sharing agreement in place and the situation. On the other hand, when working with community liaisons a summary report with aggregated results and simple graphs or figures may be more effective. Data may be presented as counts, percent of total ED visits (e.g., cases/total ED visits x100), or rates (e.g., cases/person-time). The percent of total ED visits and rates allows for comparability across regions or sub-populations.

One of the concerns with any public health surveillance system which uses medical information is the potential breach of confidentiality. This is especially of concern at smaller geographic levels (e.g., county, city, or zip code specific data) where a single case for an outcome may be present. Or small numbers may result from multiple demographic stratifications (e.g., Asian males age 5-14 years in county X). Data suppression guidelines will vary between jurisdictions and data sources/custodians. Additionally, for statistical analysis or presentation of data, numerators with less than 20 cases may produce unstable estimates (e.g., rates) [Buescher 2008; Miniño 2011]. Many jurisdictions or data holders will require suppression of data to discourage misinterpretation or misuse of statistical estimates. The level of suppression may also depend on with whom the data are being shared (e.g., internal partners, emergency management, law enforcement, the public). Check with your syndromic surveillance system coordinator prior to presenting or sharing the data.

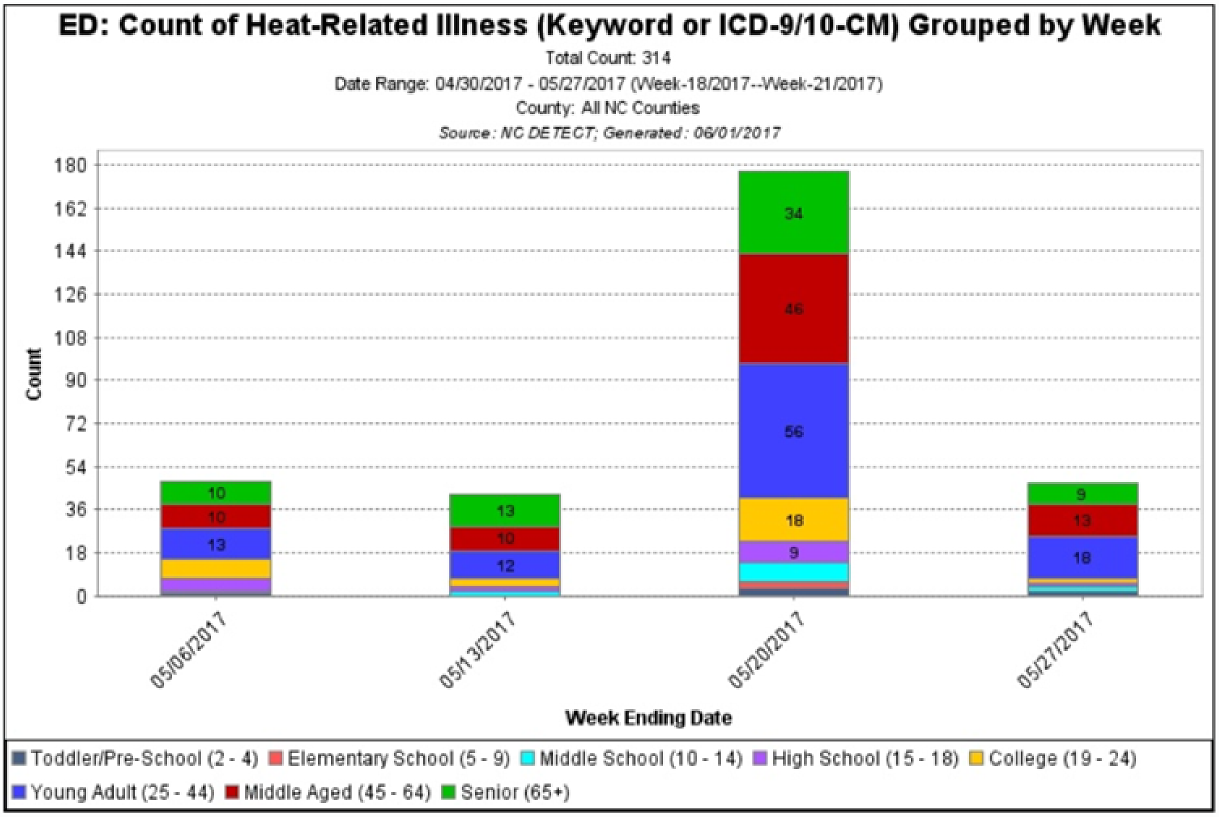

Figure 3. Figure available to authorized users of North Carolina's syndromic surveillance system as part of a heat-related illness dashboard.

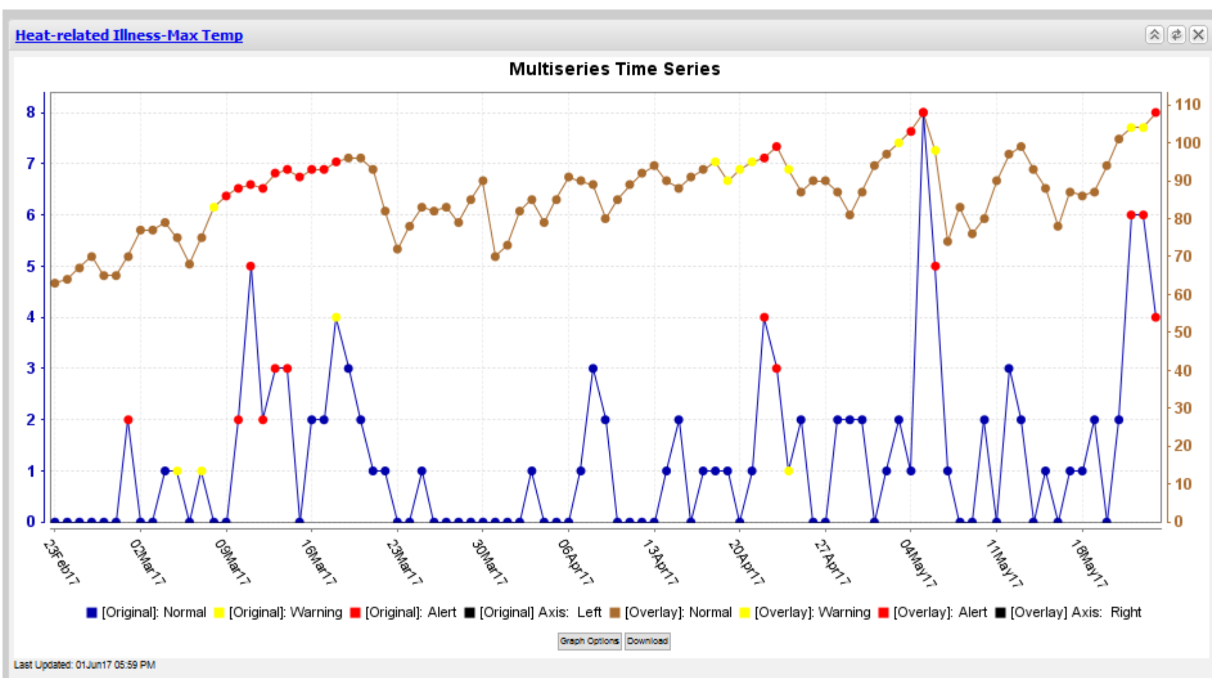

Figure 4. Example from the ESSENCE dashboard used by Maricopa County Department of Public Health to monitor heat-related illness. The time series include the heat-related illness (HRI) definition form the CSTE guidance document [CSTE 2016] (currently built into the NSSP ESSENCE CC and DD category) and an overlay of maximum and minimum (not shown) temperatures using the National Weather Service data.

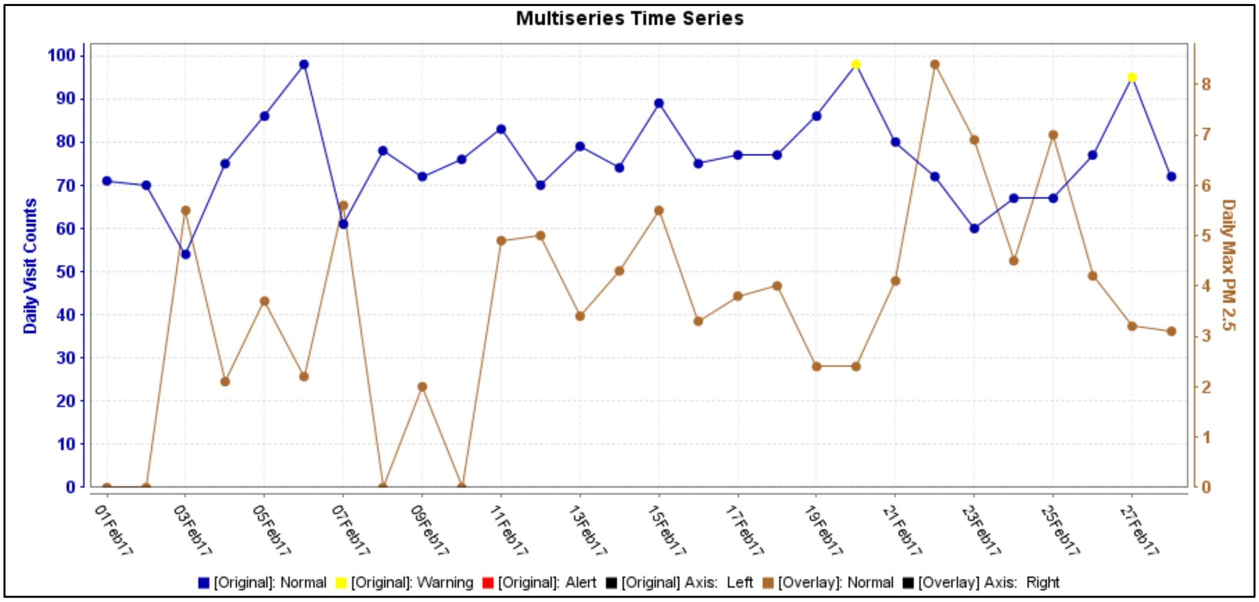

Figure 5. Asthma-like Visits from Multnomah County Residents and Portland Air Quality, February 2017. This figure provides an example of quickly visualizing a health outcome of interest with environmental data that is integrated into a syndromic surveillance system. The time series graph below shows asthma-like visits made by Multnomah County residents during February 2017 overlaid with 24-hour maximum PM 2.5 measurements (µg/m^3) in from a Portland, OR air quality monitoring station. In Oregon ESSENCE, visit information is collected from emergency departments (EDs) and urgent care centers across the state. Currently, all 60 eligible hospitals are sending ED data every day for syndromic surveillance. Some urgent care centers are currently reporting, including several in the Portland metro area. Air quality data are available from monitors statewide.

VI: IDENTIFYING AND ENGAGING POTENTIAL PARTNERS

IDENTIFYING AND WORKING WITH PARTNERS AND STAKEHOLDERS

Working with other organizations and partners increases your credibility, expands the scope of the project and project reach, potentially provides additional resources and expertise, and expands the support for your organizations objective. Potential partners and stakeholders for your syndromic surveillance project should ideally be identified as early on in the process as possible. For some projects, the initial data from your syndromic surveillance may help to identify potential partners through location information. For example, you may identify a “hot spot” in your jurisdiction where individuals develop heat-related-illness at a regularly-held event (e.g., annual marathon, annual fair or county event) that occurs during a historically warm weekend. Additionally, you may identify a sub-group of your cases that seek care, or service certain locations within your jurisdiction (e.g., a specific hospital, elderly individuals in a care home, vulnerable populations such as substance abuse patients in a residential facility). In these instances, partnering with the stakeholders and leaders of the event, or service locations will help with education campaigns as well as potential future interventions. This detailed information is often found in the admission notes (chief complaint or triage note) fields, or by a review of the medical record. Medical record review of all syndromic surveillance records can be a lengthy process depending on case counts. However, a systematic review of medical records of even a few cases can provide much needed detail that may not be captured through the fields available in the syndromic surveillance system, such the medical co-morbidities and circumstances of exposure.

Another potential source of identifying partners and stakeholders is during the first steps of the health communication process [NIH 2004]. Experts on the outcome (e.g., doctors, treating physicians) and community members (e.g., advocacy groups, community health workers) knowledgeable about the populations who most often develop these outcomes are important stakeholders to target. Explore other channels of communication and activities such as interpersonal channels (e.g., counseling or physician-patient relationships), organizational and community channels (e.g., workplace campaigns, town hall meetings), mass media (e.g., newspapers, radio, television), and social media (e.g., websites, Facebook, targeted ads). Coalitions of stakeholders often develop from the formal and informal working relationships your partners already have, thereby expanding your pool of potential partners. As your partner group grows, make sure to formalize and structure aspects of the relationship, ensure involvement in decision-making and accountability, and be flexible. This will help strengthen long-term associations with your group and create a greater commitment from your partner.

Working with partners can enhance the credibility and reach of your campaign, but identifying and working with potential partners is time consuming and may require altering your program. This can result in a loss of ownership and control of any materials that are developed. As a result, developing partnering plans and clear guidance on the roles of potential partners are essential tasks. For example, you may require feedback during gatekeeper[7] reviews of developed materials, but may not have the funding to supplement printing or promotion of the materials in their organization. Additionally, be aware that your organization may have requirements or restrictions on working with for-profit partners (e.g., local businesses, social media corporations). However, working with stakeholders has many benefits which may significantly outweigh the time and effort it may take to engage them.

PRESENTING TO PARTNERS AND STAKEHOLDERS

Regardless of when partners and stakeholders are engaged in the process of syndromic surveillance, it is important to present key findings. Early in the process of developing a syndromic surveillance approach to climate-related surveillance, presenting key findings to partners and stakeholders may help with getting "buy-in" and show the importance of the effort. Partners can also refine the work further by providing feedback to the health officials particularly on how to present and display data, as well as how to change the case definitions or keywords as needed to capture better data.

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[7] Gatekeeper reviews are reviews by individuals who are going to be using the material. [CDC 1994] For example, community health workers might review informational pamphlets created by a health department and provide feedback on how useful the material would be and any changes they would like to see. Gatekeepers may also be county health officials or people "higher up" in administration who require pre-approval before publishing.

Jurisdictions may choose to present a snapshot of the syndromic surveillance data in weekly or monthly reports to the public, or just to certain partners and stakeholders. It is important to engage all potential partners and stakeholders involved in the work; however, other groups who support or advocate for the population may also be key stakeholders in sharing and distributing the information. For example, in the case of heat-related illness and hikers, it would be important to include leaders of parks (e.g., city/county recreation parks or national parks) where heat-related illness was occurring most frequently. It would be equally as important to involve rescue associations, local hiking groups, and managers of stores that sell outdoor gear because they have more face time with potentially impacted populations. Thus, engaging stakeholders who may help with the display and promotion of your data will help with prevention and intervention campaigns.

Involving partners in the development of the interpretation and display of the data will help jurisdictions identify the needs of the communities they serve. For example, some partners may want a synopsis of the cases, while others would like a one-page report with key messages to distribute to their email lists. Any report presented to partners should include any limitations of the data, as well as contact information for individuals who wish to receive more information.

Insert 5: Informing planning and enhancing surveillance for extreme weather

CDC funding helped the New York City (NYC) Climate and Health Program (CHP) improve planning for weather-related power outages and hurricanes, and helped augment NYC's internal surveillance capacity for these events. An assessment of the potential health effects of coastal storms was conducted, including a review of vulnerable populations, using literature review and mapping of vulnerability indicators. Superstorm Sandy, the most damaging extreme weather event to strike the city in recent decades, took place in October 2012 as temperatures were cooling, and just before a significant temperature drop and a Nor'easter further impacted the City. Hundreds of thousands of people in coastal communities most affected by the storm surge were without one or more essential utilities (electricity, heat, or running water) in some cases for several weeks.

NYC had developed and evaluated a syndromic surveillance definition for cold-related illness prior to the storm that they were quickly able to adapt to monitor for hypothermia and other cold-related illness such as frostbite. This complemented existing carbon monoxide (CO) surveillance, which tracked exposures using ED data and Poison Control Center (PCC) calls. The surveillance systems were used to detect trends and, as increases in cases of cold-related illness and CO poisoning were observed, information was provided, in near-real time, to inform public messaging about the risks of living in unheated housing. [Lane 2013]

Since then, NYC CHP has continued to improve the surveillance systems, creating cold-related illness surveillance regression models that incorporate weather data and control for time trends. [Personal Communication: NYC Department of Health, March 2017]

VII: STRENGTHS AND LIMITATIONS

STRENGTHS

The success of syndromic surveillance can be contributed to several strengths. One is the increasing completeness of the data. With the expansion of the National Syndromic Surveillance Program (NSSP), the CDC estimates that as of May of 2017, 65% of the ED visits in the United States are captured in their surveillance system. NSSP receives data from more than 4,000 facilities. Currently, 47 sites in 40 states participate in the NSSP. At least 14 sites are working on local data feeds with plans to transmit data to the BioSense Platform (i.e., will be available in NSSP ESSENCE tool) soon. Many others are scheduled to onboard later in 2017 [CDC/NSSP 2017]. Additionally, there are many jurisdictions with their own syndromic surveillance system.

Another strength is timeliness. Most of the ED visits are received by public health within 12 hours of initial activity [Hope 2006]. This timeliness provides situational awareness for emerging threats, including weather related events. Many of the surveillance systems in use now are also flexible and allow the user to create their own queries looking for key words that may identify visits related to rapidly changing conditions. This flexibility helps users use local or regional terminology most likely to be used in their event [CSTE 2016]. For example, coastal states are more likely to need the ability to look for visits related to hurricanes while northern states are more likely to look for visits related to snowstorms.

Syndromic surveillance can also help capture social disparities experienced from climate change. Patients who rely disproportionately on the ED are also particularly vulnerable to climate change [Hess 2009]. Information from the data can help responders identify the populations most at risk and plan accordingly in advance of expected events.

LIMITATIONS OF USING SYNDROMIC SURVEILLANCE: IN GENERAL AND FOR CLIMATE-RELATED EXPOSURES

Although syndromic surveillance represents a timely source of data regarding health outcomes, its use has a number of limitations. First, because syndromes are not confirmed via clinical criteria or laboratory testing, they should not be interpreted as definitive case counts. The identified visits are generally[8] visits where the patient has symptoms of the outcome. Records classified into a syndrome based on pre-clinical information may be misclassified. Due to the nature of categorizing pre-clinical information, it is not definitive that all ED visits for a certain case definition can be attributed to a climate related event, particularly when a discharge diagnosis is not available. Furthermore, due to the nature of self-reported chief complaints, some visits that are associated with the event may not be included because of a vague

[8] The exception is cases identified by discharge diagnosis codes, depending on the quality of received discharge diagnosis codes. Before making any assumptions about discharge diagnosis codes – speak with your syndromic surveillance coordinator about data quality.

chief complaint. For example, an ED visit for carbon monoxide poisoning with a chief complaint of dizziness may not be classified as a carbon monoxide syndrome case.

The PPV of syndrome definitions have been shown to vary based on the characteristics of the condition being monitored, the population being surveilled, and other factors [CSTE 2016]. In the context of intense media coverage of a health issue, increases in detection of outcomes may reflect changes in healthcare-seeking behavior rather than actual increases in disease [Elliot 2016]. Moreover, when free text fields are used to define syndromic surveillance case definitions, typographical errors, misspellings, abbreviations, and acronyms in electronic health records may lead to undercounting of outcomes [Shapiro 2004; O'Connell 2010]. The alert algorithms that are a feature of some syndromic surveillance systems may have a low PPV [Guasticchi 2009] and be insufficiently sensitive for the detection of some types of disease outbreaks [O'Connell 2010; Balter 2005].

A third limitation is that EDs that contribute data to syndromic surveillance systems are not representative nationally or in many geographic areas–especially rural areas [Coates 2016]. Further, health outcomes attended by emergency medical services without transport to a hospital are not typically captured in a syndromic surveillance system, which may limit the use of syndromic surveillance for certain outcomes of interest. In addition, while hospital (or ED) participation is increasing generally, not all hospitals in a jurisdiction may participate in the system. As a result, the captured visits may not represent all syndrome cases and calculated rates will be biased downward (i.e., underestimated). However, the data can still be used to describe and inform trends in syndrome presentation within the jurisdiction.

Another limitation of syndromic surveillance is the need for significant staff time to individually review records and alerts. This is a particularly significant barrier for local health departments (LHDs), although lack of access to the syndromic surveillance systems themselves [Chugtai 2016] and lack of informatics skills among LHD staff [DeVore 2016; Massoudi 2016] also inhibit effective use of these systems. Modest increases in LHD use of syndromic surveillance data have been observed after the implementation of system improvements including LHD-specific dashboards to facilitate data visualization and increased distribution of LHD-specific surveillance data by a state public health agency [Samoff 2014; Fangman 2015], but further research is needed to identify system improvements that increase use of syndromic surveillance data for public health decision-making. Finally, the setting of appropriate thresholds for alerts that require response may require significant time and expertise.

VIII. CONCLUSION

Climate change impacts a vast array of health outcomes, ranging from chronic diseases to infectious diseases to injuries. A strong multi-dimensional surveillance system is required to meet the challenge of protecting the health and well-being of our populations. While syndromic surveillance systems should not be used as a replacement for traditional epidemiologic surveillance, it can be a valuable part of a jurisdictions overall surveillance by providing near real-time detection and monitoring of disease outbreaks and public health emergencies, monitoring of disease trends, case finding, seasonal event response, situational awareness, program management, and development of summary reports. Historically, much of the weather- and climate-related surveillance has occurred after an event, sometimes significantly after an event (e.g., a retrospective analysis of all-cause mortality after an extreme heat event). By leveraging the near real-time functionality of syndromic surveillance, public health practitioners can assess baseline healthcare burden before a forecast event, in addition to during or immediately after one.

This guidance document provides the initial steps for jurisdictions to develop and expand their surveillance of weather- and climate-related health outcomes. The document does not cover all options, so the workgroup encourages jurisdictions to continue to develop and share new ideas or methods via workgroups, conferences, and publications. Both the Council of State and Territorial Epidemiologist (CSTE: www.cste.org) and the International Society for Disease Surveillance (ISDS: www.healthsurveillance.org) have forums, communities of practice (CoP), and additional resources available on their websites. Finally, Public Health Reports recently published a syndromic surveillance supplement which includes numerous articles on weather- and climate-related syndromic surveillance [Yoon 2017].

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APPENDIX A

NC Heat Report

North Carolina Heat Report

May 21-27, 2017

Key Points

- Approximately 43 emergency department visits for heat-related illness were observed
- Daily maximum heat indices ranged from 75.9°F to 93.3°F (median = 78.1°F) at Raleigh-Durham International Airport (RDU)
- Common references in emergency department visit notes were for working outdoors (e.g., painting, roofing) and recreation (e.g., yard work, going to the beach, outdoor entertainment events).

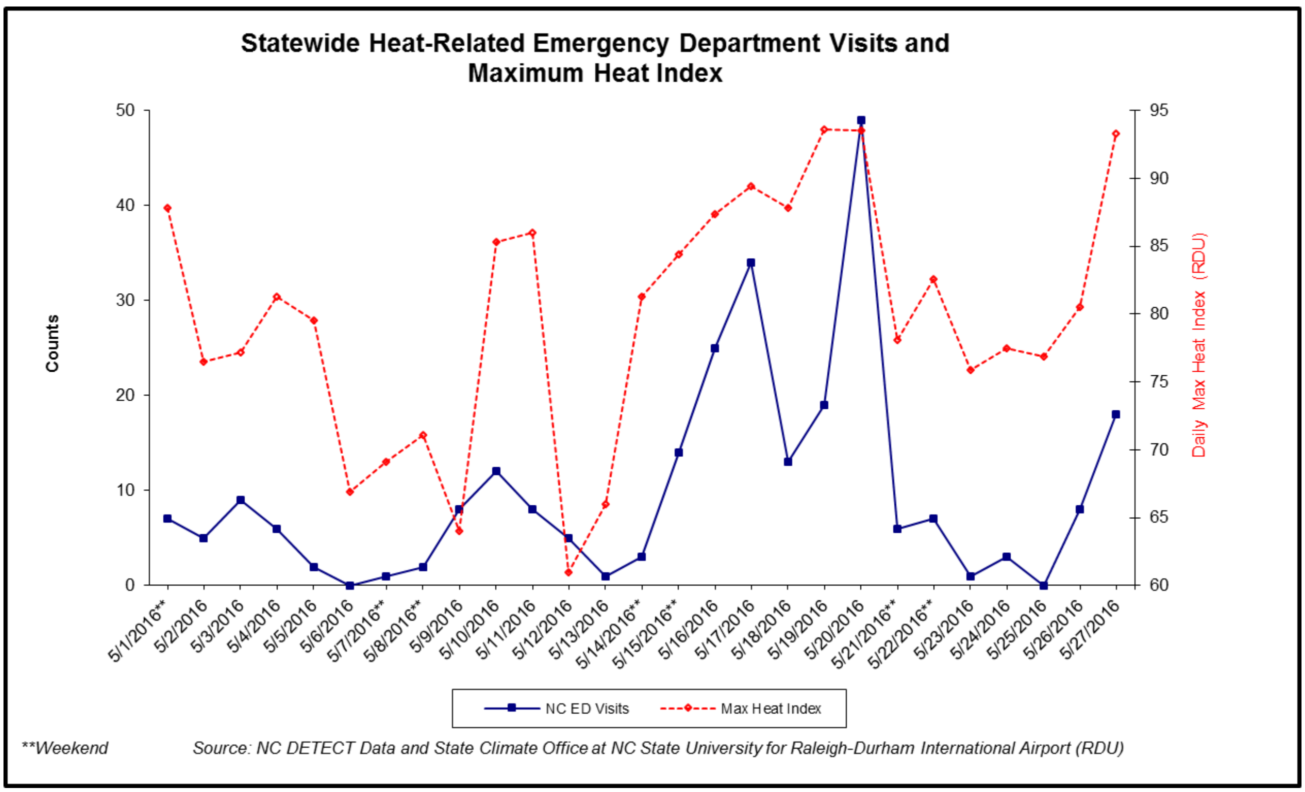
Season to Date (May 2017)

- Approximately 266 heat-related illnesses have been identified in emergency department visit records (figure 1)
- 79% of illness was among males, mostly aged 25-64 (figure 2)

Regional Data

- 54% of all visits were seen in hospitals in the Piedmont region
- 13% of all visits were seen in hospitals in the Sandhills sub-region[1]

Figure 1. Emergency department visits for heat-related illness and daily maximum heat index (RDU airport), 5/1/17 to 5/27/17, North Carolina.



[1]The Sandhills sub-region is comprised of the following counties from the Piedmont and Coastal regions: Bladen, Cumberland, Harnett, Hoke, Lee, Montgomery, Moore, Richmond, Robeson, and Scotland.

Figure 2. Emergency department visits for heat-related illness by age group, 5/1/17 to 5/27/17, North Carolina.

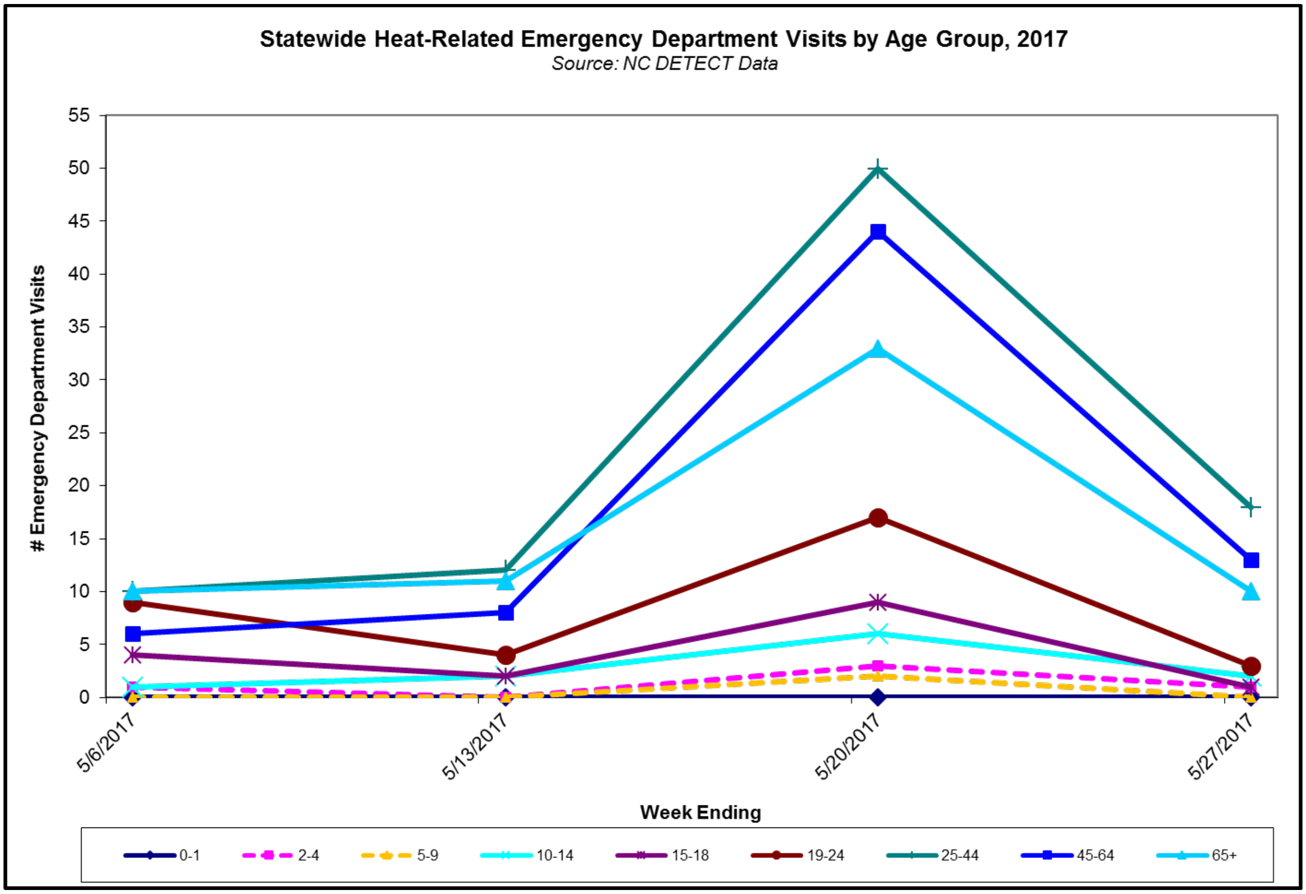
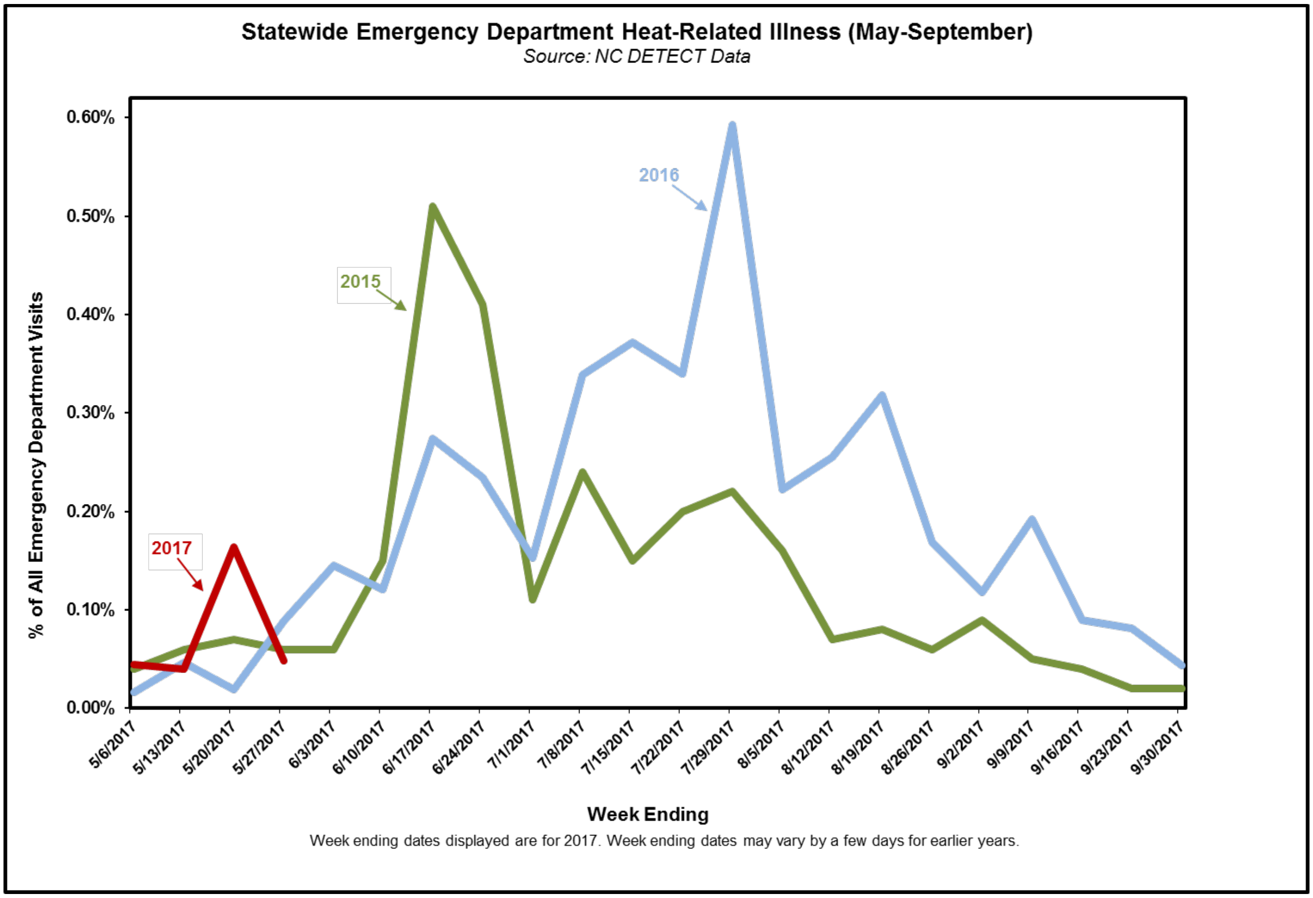


Table 1. Emergency department visits for heat-related illness by age group, 5/21/17 to 5/27/17, North Carolina.

	N	(%)
Sex		
Male	34	(79)
Female	9	(21)
Age Group (yrs)		
0-14	<5	--
15-18	<5	--
19-24	<5	--
25-44	16	(37)
45-64	14	(33)
65+	8	(19)

NOTE: Counts and percentages are not reported when the total number of emergency department visits is less than 5

Figure 3. Emergency department visits for heat-related illness for selected years, 2015 to 2017, North Carolina.



NOTE: Emergency department visit records and maximum heat indices were obtained from NC DETECT and the State Climate Office at NC State University, respectively. Heat-related illness is captured through a near real-time keyword search for 'heat,' 'hot,' 'hyperthermia,' 'heat cramp,' 'heat exhaustion,' 'heat stroke,' and 'sun stroke' in chief complaint or triage notes of emergency department records or a diagnosis code for heat-related illness. These figures present an estimate of the number of emergency department visits for heat-related illness. Please contact lauren.thie@dhhs.nc.gov for more information.