



RE-Powering Critical Infrastructure

A Study to Determine Whether RE-Powering Sites Could Meet the Emergency Energy Needs of Wastewater Treatment Plants



Table of Contents

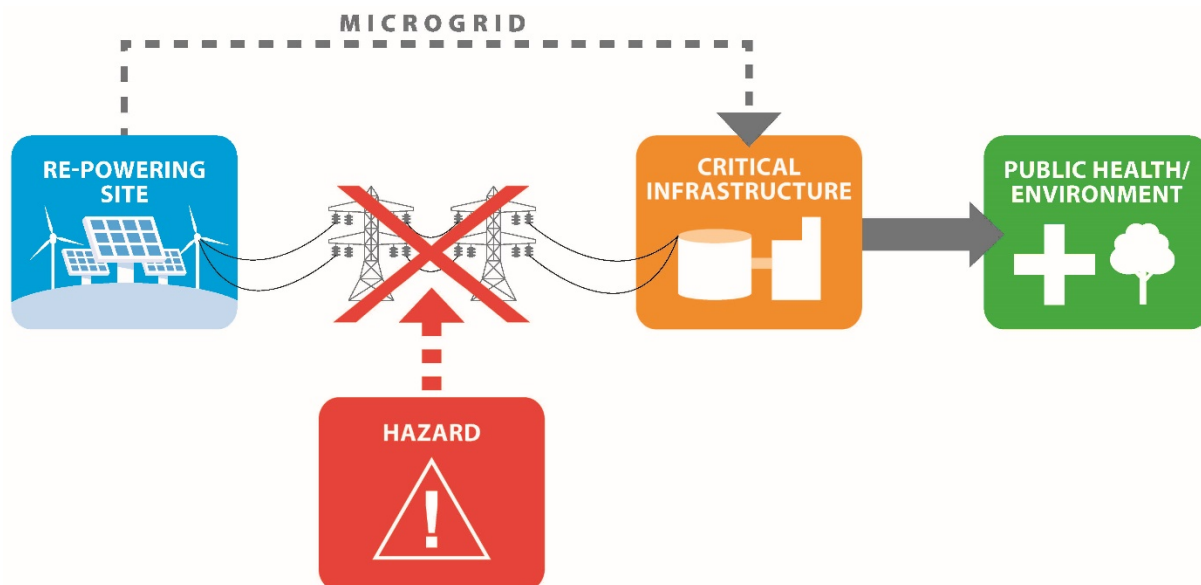
| | |
|--|----|
| Introduction | 1 |
| Purpose | 2 |
| Screening Methodology Overview..... | 2 |
| Vulnerability Screening | 5 |
| Proximity Screening | 5 |
| Economic Screening | 5 |
| Needs Screening | 6 |
| Summary of Findings – Application of Methodology to WWTPs..... | 7 |
| Vulnerability and Proximity at the National Scale | 7 |
| Detailed Findings by Region | 9 |
| Discussion..... | 14 |
| Application to Other Types of Infrastructure..... | 15 |
| Conclusion..... | 16 |
| Appendix A: Approach for Developing Screening Criteria | 18 |
| Vulnerability Screening | 18 |
| Proximity Screening | 21 |
| Economic Screening | 22 |
| Needs Screening | 24 |
| Appendix B: Rationale and Information Sources for Proposed Threat Categorization | 27 |
| Appendix C: Datasets Used for the Analysis | 36 |
| Appendix D: Additional Summary of Findings Tables | 39 |

Introduction

EPA’s RE-Powering America’s Land Initiative encourages renewable energy development on current and formerly contaminated lands, landfills, and mine sites (RE-Powering sites) when such development is aligned with the community’s vision for the site. RE-powering can provide cleaner energy sources in areas of high demand, while returning land to productive use. RE-Powering sites also may have attributes that can lower renewable energy development costs and shorten development timeframes (for example, proximity to infrastructure).

As they are often located within or near population centers, RE-Powering sites also offer opportunities for meeting the specific energy demands of nearby off-takers, such as industrial plants, universities, and as this analysis suggests, critical infrastructure. For the purposes of this analysis, critical infrastructure includes assets that are key for maintaining public health and safety, such as wastewater treatment plants (WWTPs), drinking water treatment plants, hospitals, or emergency shelters. Critical infrastructure assets require reliable energy sources, especially in emergencies. Renewable energy in combination with a decentralized electricity grid can make communities more resilient. Benefits of this approach could include protection against failure of antiquated grids or, at least, isolation of specific facilities against widespread outages, including outages associated with natural disasters and other events (see Figure 1).

Figure 1. Illustration of RE-Powering Site Support of Infrastructure Critical to Protecting Human Health and the Environment



Scientific studies indicate that extreme weather events such as heat waves and large storms are likely to become more frequent or intense in the future.¹ Owners and end users of critical infrastructure are recognizing the need to protect against power outages created by these more frequent and intense

¹ Source: EPA, “[Climate Change Indicators in the United States](#)”.

events, in both the long and short term. The ability to provide energy security, surety, resiliency, and reliability through any event is essential to protecting human health and the environment. WWTPs protect human health and ecosystems, and disruptions to WWTP functioning can be devastating. The disruption to Houston area WWTPs during hurricane Harvey in 2017, for example, exacerbated the pooling and stagnating of raw sewage.

Several creative examples already exist for supporting critical infrastructure with a microgrid or islanded power (see Creative Solutions text box). However, the potential for the widespread application of RE-Powering sites was previously unknown. Key objectives of the analyses described in this document were to investigate this potential as well as demonstrate a replicable methodology for identifying RE-Powering sites that could support renewable energy systems that could meet the emergency energy needs of critical infrastructure. As reported in the [Summary of Findings](#), RE-Powering sites are widespread, often located near critical infrastructure (e.g., in industrial areas), and, in the case of WWTPs, can frequently support energy needs for emergency operations.

While this specific analysis focuses on WWTPs, the methodology and analysis are intended to be expandable to other types of critical infrastructure. This document describes the methodology and presents preliminary findings and results. Limitations and potential refinements are also discussed.

Purpose

To develop and demonstrate a methodology that could be used to evaluate the potential for RE-Powering sites to support critical infrastructure assets, including in emergency situations, and to identify specific EPA-screened sites with the best potential for supporting wastewater treatment infrastructure.

Screening Methodology Overview

RE-Powering site data come from the August 2015 update of [EPA's RE-Powering Mapper](#). As part of the RE-Powering Mapper effort, EPA used screening criteria developed in collaboration with the National Renewable Energy Laboratory (NREL) to pre-screen more than 80,000 sites for renewable energy potential. The RE-Powering Mapper screening criteria consider site size (acreage), renewable energy resource availability, and distances to nearest road and transmission lines.

A total of 22,299 RE-Powering sites with potential to provide at least large-scale solar or wind power sufficient to export energy to the grid and support critical infrastructure were included in the analysis

Creative Solutions

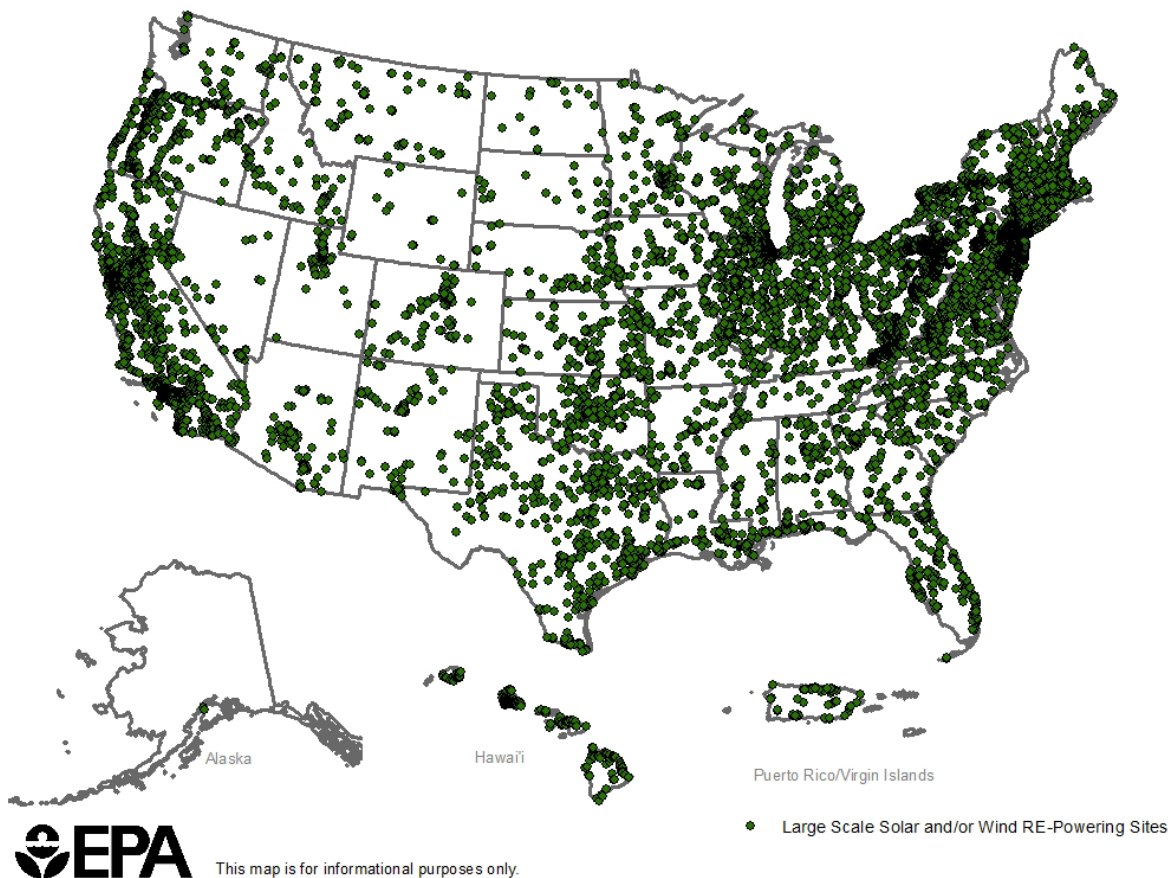
In Washington, D.C. the District Department of Energy and Environment indicates that total on-site generation at Blue Plains Advanced WWTP, "[closely matches critical process requirements](#)." Facility managers at Blue Plains are interested in eventually islanding the WWTP renewable energy systems, so that they can continue to, "[operate in the event of a wider power outage](#)."

In late 2015, the City of Santa Rosa, CA, [announced a partnership with Trane](#) to reconfigure the city's Laguna WWTP as a microgrid. The project, supported in part by a \$5 million grant from the California Energy Commission, will include solar power and energy storage.

In addition, while not a WWTP, [Stafford Hill Solar Farm](#), a former landfill in Rutland, VT has a solar photovoltaic system with battery storage that serves as a microgrid. The system provides power to the city's emergency center at the high school, offering another example of how RE-Powering sites can support critical infrastructure needs.

(see Figures 2 and 3)^{2,3} These 22,299 sites represent a total potential renewable-energy-generating capacity of over 6.7 million megawatts (MW). Over half of these potential RE-Powering sites are in the Northeast and Ohio Valley, whereas 71% of the renewable energy generation potential is associated with sites in the Southwest, Northwest, and West. Sites in the Northeast and Ohio Valley tend to be smaller and more widely distributed, while sites in western states tend to be larger, with greater potential for renewable energy capacity at each site.

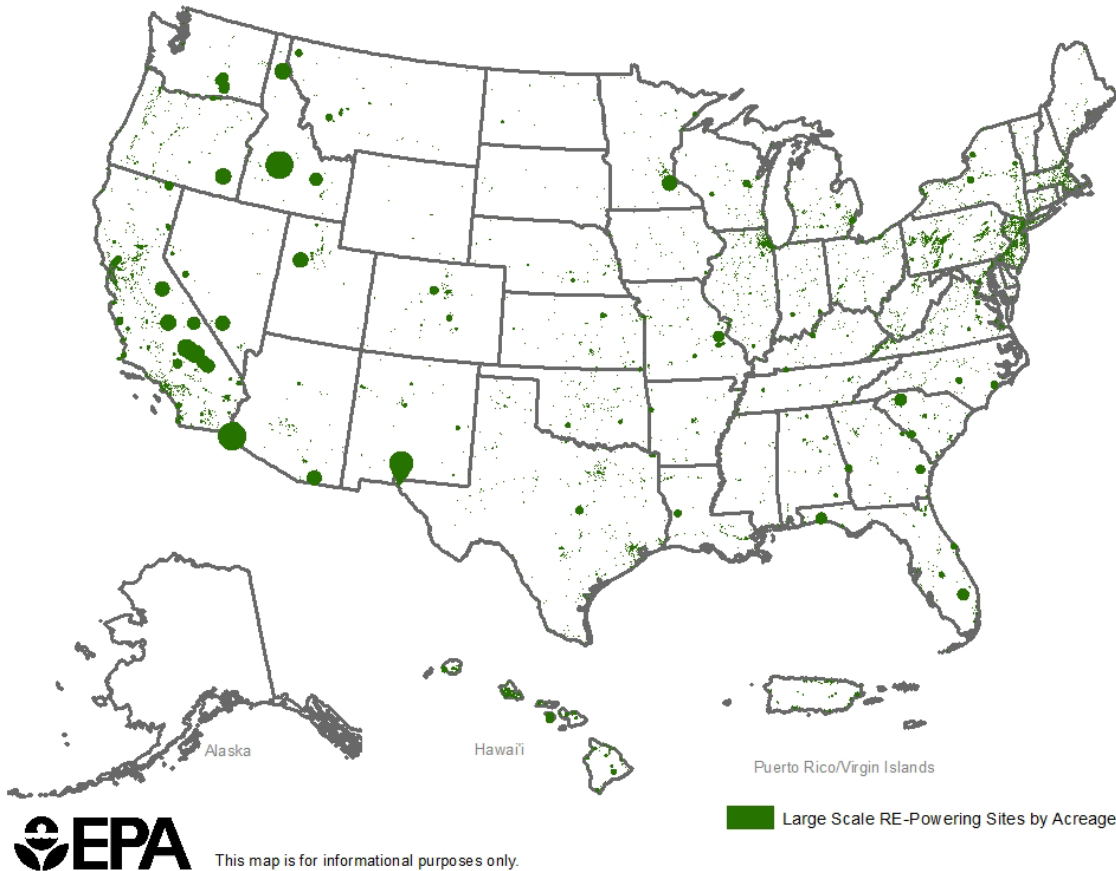
Figure 2: RE-Powering sites with at least large-scale PV and wind potential



² For the purposes of this analysis, this includes potential RE-Powering sites classified as utility-scale PV, large-scale PV, utility-scale wind, large-scale wind, and 1–2 turbine wind sites. These classifications are defined in *Data Documentation for Mapping and Screening Criteria for Renewable Energy Generation Potential on EPA and State Tracked Sites RE- Powering America's Land Initiative* (https://www.epa.gov/sites/production/files/2015-04/documents/repowering_mapper_datadocumentation.pdf).

³ Note the higher capacity value from either wind or solar was used for the purposes of the analysis.

Figure 3: RE-Powering sites with at least large-scale PV and Wind potential by size



This analysis applies a screening approach to the Mapper data to identify RE-Powering sites that are:

- Located in areas that are likely to experience power outages – *Vulnerability Screening*;
- Near a WWTP – *Proximity Screening*;
- Economically suited for siting renewable energy – *Economic Screening*; and
- Most likely to meet the energy needs of the facility being supported – *Needs Screening*.

Below is a summary of the screening process as applied to complete the WWTP analysis. Appendices A and B provide more detailed information about the approach for developing each of the screening criteria. Appendix C describes the datasets used to develop the screening criteria. Appendix D contains additional findings.

Vulnerability Screening

Vulnerability screening identifies areas at high risk for potential extended power outages due to the following types of hazards: hurricanes/tropical storms; tornadoes; coastal flooding, including effects of storm surge and sea level rise (SLR); inland flooding; earthquakes; and wildfires. The approach characterizes “vulnerability” in terms of relative threat (the potential that a hazard will cause a power outage) and relative probability of exposure to the threat. The threat rating relates to how extreme an event is (for example, high wind speeds in a tropical storm would be a “high” threat), while probability represents the likelihood of a specific type of event. The probability of an area being exposed to a hazard at different threat levels was identified using data sources that are readily available for national geospatial analysis. Threat-probability combinations were used to create five relative vulnerability screening categories, ranging from high threat/high probability to low threat/low probability. [Appendix A: Approach for Developing Screening Criteria – Vulnerability Screening](#) describes the analysis approach and provides details related to threat and probability determinations.

Proximity Screening

Proximity screening is used to identify RE-Powering sites within one mile of a critical infrastructure asset. For the WWTP analysis, this resulted in one-to-many relationships, where multiple RE-Powering sites were identified in proximity to a WWTP facility. This also resulted in some instances where multiple WWTPs were in proximity to a single RE-Powering site.

Economic Screening

Economic screening is used to determine suitable sites based on whether the cost of developing renewable energy installations at these sites would be competitive with other electricity-generating technologies. To develop the economic screening criterion, electricity pricing data for utility service and pricing territories where potential sites are located were compared to regional levelized cost of electricity (LCOE) estimates developed by the U.S. Energy Information Agency (EIA). The analysis considered two renewable energy technologies (solar and wind) at various scales as defined by the RE-Powering program: utility-scale solar photovoltaics (PV), large-scale solar PV, utility-scale wind and large-scale wind, and 1–2 turbine wind (see Table 1 for screening criteria, including estimated capacity and size).⁴ Four categories were developed to rank the relative economic competitiveness of these technologies, ranging from very competitive to not competitive.

⁴ See [Data Documentation for Mapping and Screening Criteria for Renewable Energy Generation Potential on EPA and State Tracked Sites RE-Powering America’s Land Initiative](#) for more information on the renewable energy technology and screening requirements. Note that the screening criteria outlined in Table 1 and used to populate the RE-Powering Mapper was updated in the Fall of 2018. This analysis, however, was completed prior to this update and reflects the criteria used in the previous version of the mapping tool, which was issued in August 2015.

Table 1: Screening Criteria for Solar PV and Wind

| Renewable Technology | Estimated RE Project Capacity Range | Renewable Energy Resource Availability | Acreage (acres) | Distance to Transmission (miles) | Distance to Graded Roads (miles) |
|----------------------|-------------------------------------|---|-----------------|----------------------------------|----------------------------------|
| Solar PV | | Direct Normal (kWh/m ² /day) | | | |
| Utility scale | > 6.5 MW | ≥ 5.0 | ≥ 40 | ≤ 10 | ≤ 10 |
| Large scale | > 300 kW | ≥ 3.5 | ≥ 2 | ≤ 1 | ≤ 1 |
| Wind | | Wind speed (m/s) | | | |
| Utility scale | > 10 MW | 5.5 m/s at 80 m | ≥ 100 | ≤ 10 | ≤ 10 |
| Large scale | > 5 MW | 5.5 m/s at 80 m | ≥ 40 | ≤ 10 | ≤ 10 |
| 1-2 Turbine sites | > 1 MW turbine | 5.5 m/s at 80 m | ≥ 2 | ≤ 1 | ≤ 1 |

Needs Screening

Needs screening refers to the estimated generation potential of RE-Powering sites relative to the energy needs of the associated critical infrastructure. The screening considers the energy required to protect human health, safety, and the environment in an emergency (relative to full operating power). Because different types of infrastructure have different power requirements to maintain critical operations, the needs screening step is infrastructure-specific.

WWTP data was collected from the 2012 [EPA Clean Watersheds Needs Survey](#) (CWNS). Facilities were categorized according to major WWTP types, and information regarding average electric energy intensities, including adjustment factors for levels of treatment and average flow, was used to estimate the electric energy intensity for each WWTP in the analysis. Emergency needs consider that the RE-Powering installation would likely only need to supply a level capable of powering critical operations protective of human health, safety, and the environment through an emergency. Emergency power requirements were estimated based on electric energy intensity, average daily flow rate data from the CWNS, and an adjustment factor for emergency power load. [Appendix A: Approach for Developing Screening Criteria – Needs Screening](#) provides more details on emergency power loads.

Summary of Findings – Application of Methodology to WWTPs

Overall, the analysis indicates notable potential for supporting WWTPs with renewable energy on contaminated sites across the United States.

The results of the WWTP analysis also highlight the importance of considering multiple criteria when screening potential RE-Powering sites for their ability to support energy needs for critical infrastructure. The attractiveness of any site depends in part on the priorities under consideration—for example, is it more important that a WWTP is vulnerable to outages from a high-severity hazard event, or that the site is proximal to more than one WWTP? Economic suitability is also important. Even if a site can support the nearby WWTP, it may still be difficult to develop wind or solar if economic returns on those technologies are not competitive.

Vulnerability and Proximity at the National Scale

Extreme weather events can happen anywhere, but they commonly follow patterns and occur in specific regions of the country (see maps in Figure 4). For example, hurricanes tend to be more frequent along the eastern and gulf coast states, tornados cluster in the mid-west (e.g., tornado alley), earth quakes have a higher probability in California along the San Andreas Fault and the mid-west along the New Madrid Fault, flooding is prominent along waterways and lower elevations, and wildfires can happen anywhere but tend to be more common in the western U.S. where conditions are more favorable with fuel and lower humidity. The vulnerability layer is “infrastructure-neutral” and allows for replicating or “scaling up” the study to include different types of critical infrastructure.

In this case, a total of 1,563 out of 16,000 unique wastewater structures mapped in locations that rated at least 4 (“high threat/moderate probability” or “moderate threat/high probability”) for one or more hazards. A total of 135 WWTPs in 24 states were ultimately identified (see Table 2 notes and Figures 5 and 6). WWTPs have average daily flows ranging from 0.1 million-gallons-per-day (MGD) to 812 MGD. Over half of the WWTPs included in the analysis have an average daily flow of less than 10 MGD. As reported in Table 2, 340 RE-Powering sites with at least large-scale capacity for wind and solar are within one mile of WWTPs in our study.

Table 2: Summary of Evaluated WWTPs and RE-Powering Sites

| | |
|---|--------|
| All RE Powering Sites Evaluated | 81,667 |
| Universe of Wastewater Infrastructure from CWNS WWTPs Evaluated | 16,691 |
| WWTPs Selected for Analysis* | 135 |
| RE Powering Sites that meet all screening criteria** | 340 |

* WWTPs selected for inclusion in the analysis were based on visual verification of treatment capacity and attribute data, indicating treatment level. Infrastructure that appeared to merely collect or channel wastewater was not included. Major urban areas, with clustering of RE-Powering sites, were targeted for this sample.

**RE-Powering sites within one mile of WWTPs (proximate screening) with a minimum vulnerability category of 4 (vulnerability screening), a minimum Capacity-to-Power Ratio of 1 (needs screening), and a minimum economic sustainability of Possibly Competitive or above (economic screening). See [Appendix A: Approach for Developing Screening Criteria](#) provides details related to screening categories.

Figure 4: Maps depicting areas of high hazards used for this analysis.

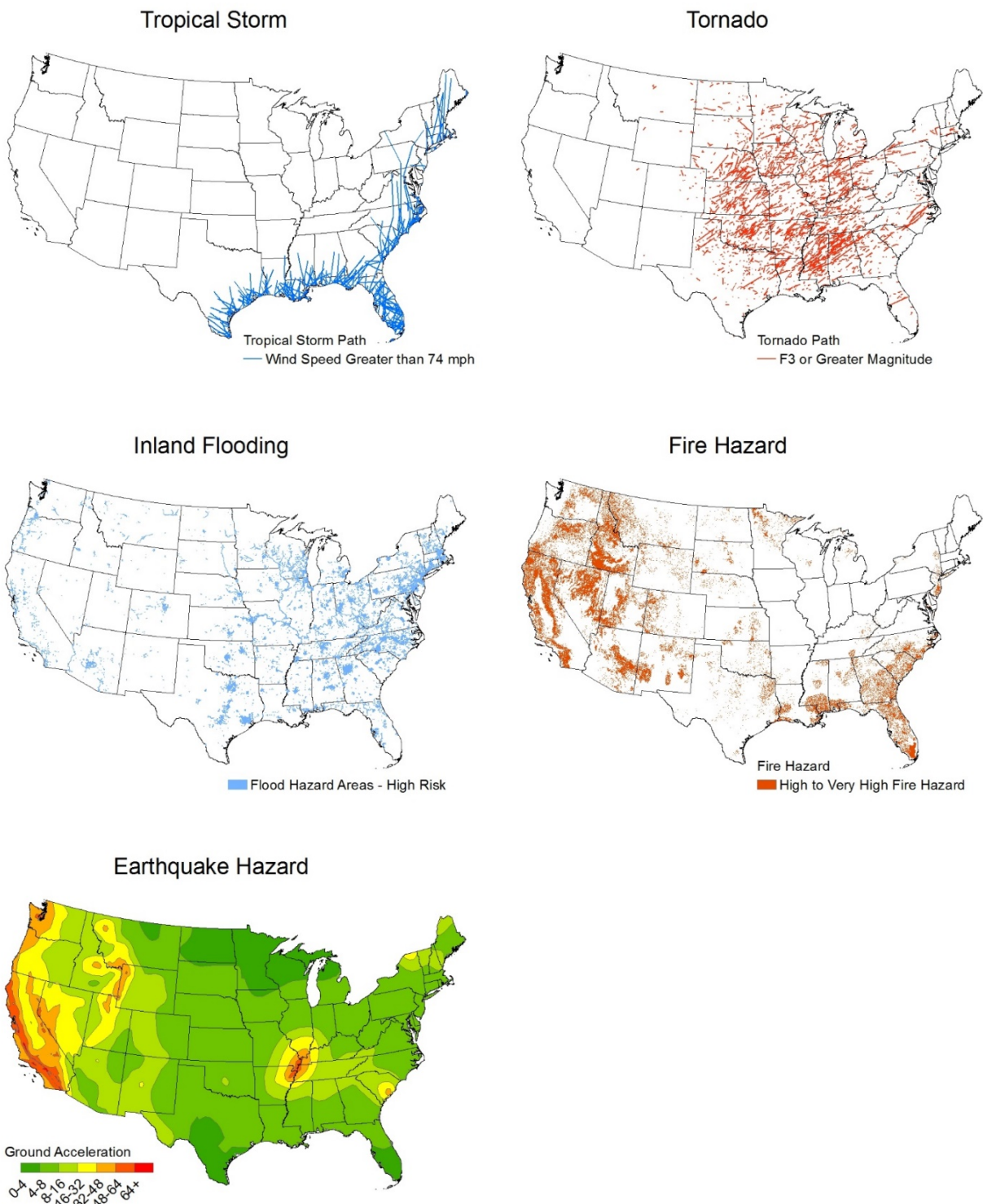
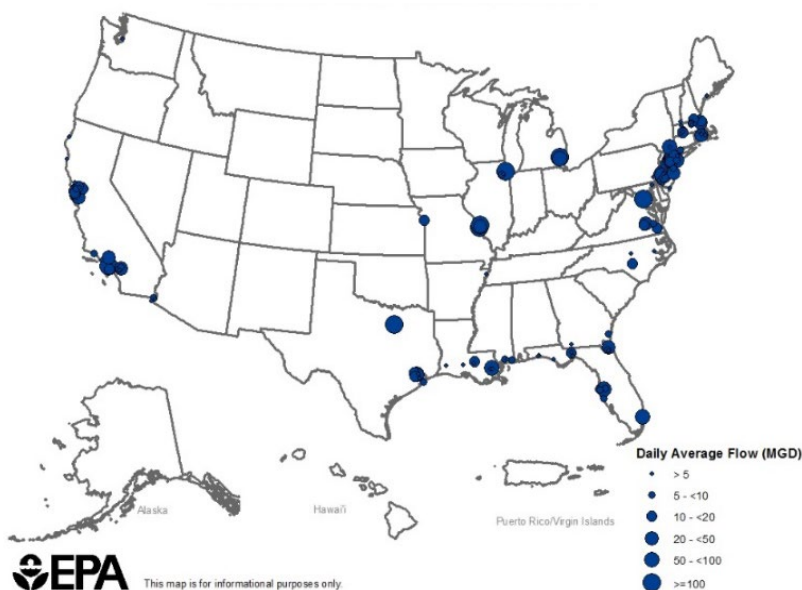


Figure 5: CWNS WWTPs Evaluated



Figure 6: CWNS WWTPs Evaluated Daily Average Flow (MGD)



Detailed Findings by Region

This section describes the relationship between the identified WWTPs and RE-Powering sites that mapped to within one mile of a WWTP in four climate regions⁵ of the United States. A metropolitan location was selected in each region to highlight the spatial relationship between the critical infrastructure and the RE-Powering sites.

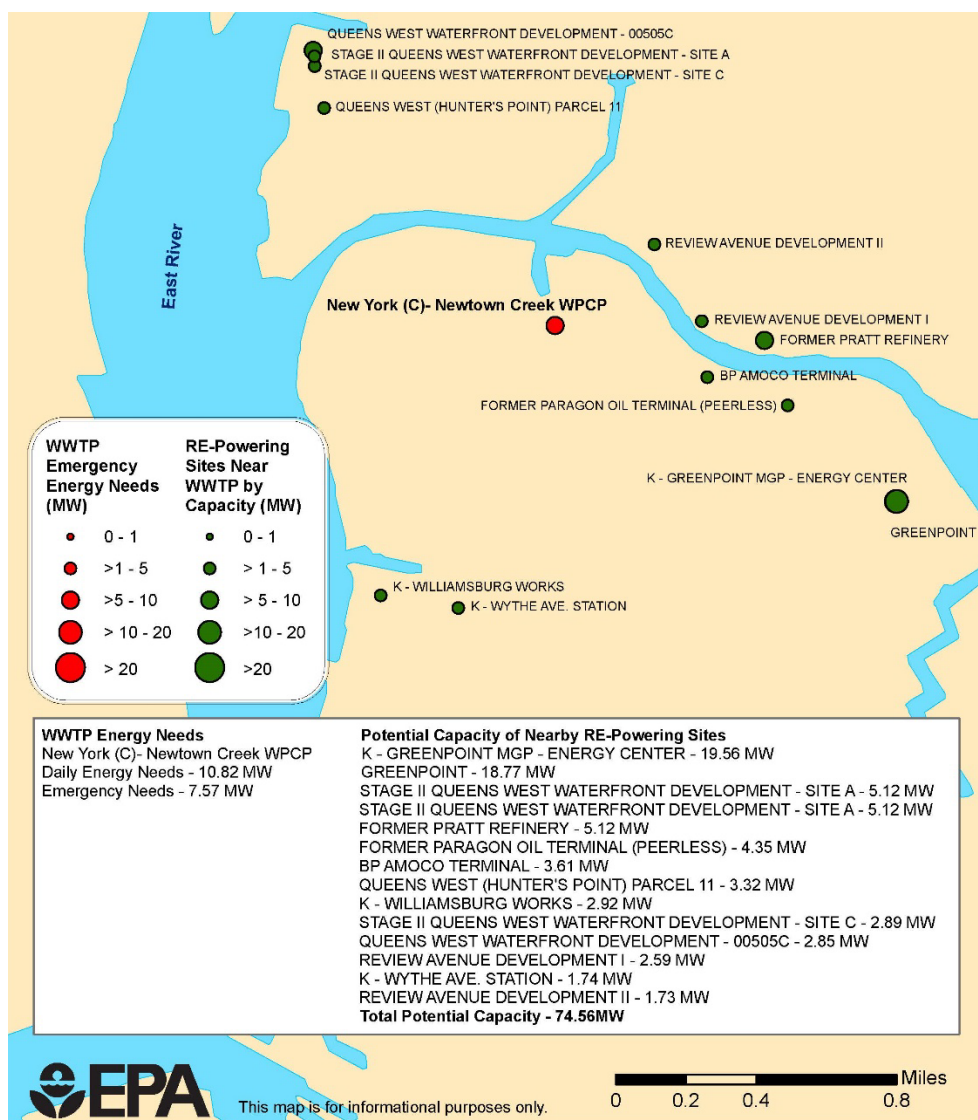
⁵ The National Centers for Environmental Information have identified nine climatically consistent regions within the contiguous United States which are useful for putting current climate anomalies into a locational and historical perspective (<https://www.ncdc.noaa.gov/monitoring-references/maps/us-climate-regions.php>).

Northeast

The Northeast region comprises 11 states: Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. While this region is susceptible to multiple hazards, the primary hazards of concern are tropical storms and coastal and inland flooding. Based on the vulnerability analysis, 51 WWTPs in the Northeast region are rated at least 4 (“high threat/moderate probability” or “moderate threat/high probability”) for tropical storms, 37 for coastal flooding, and 47 for inland flooding.

Across the region, there are 135 RE-Powering sites with economically competitive solar or wind capacity that is sufficient to support the emergency energy needs of nearby WWTPs. In addition to meeting the emergency energy needs, there are 116 RE-Powering sites with economically competitive solar and/or wind capacity that is sufficient to support the daily energy needs of nearby WWTPs. Figure 7 illustrates the spatial proximity of the sites and favorable screening results.

Figure 7: Comparison of WWTPs and nearby Potential RE-Powering Sites in the New York, New York Area

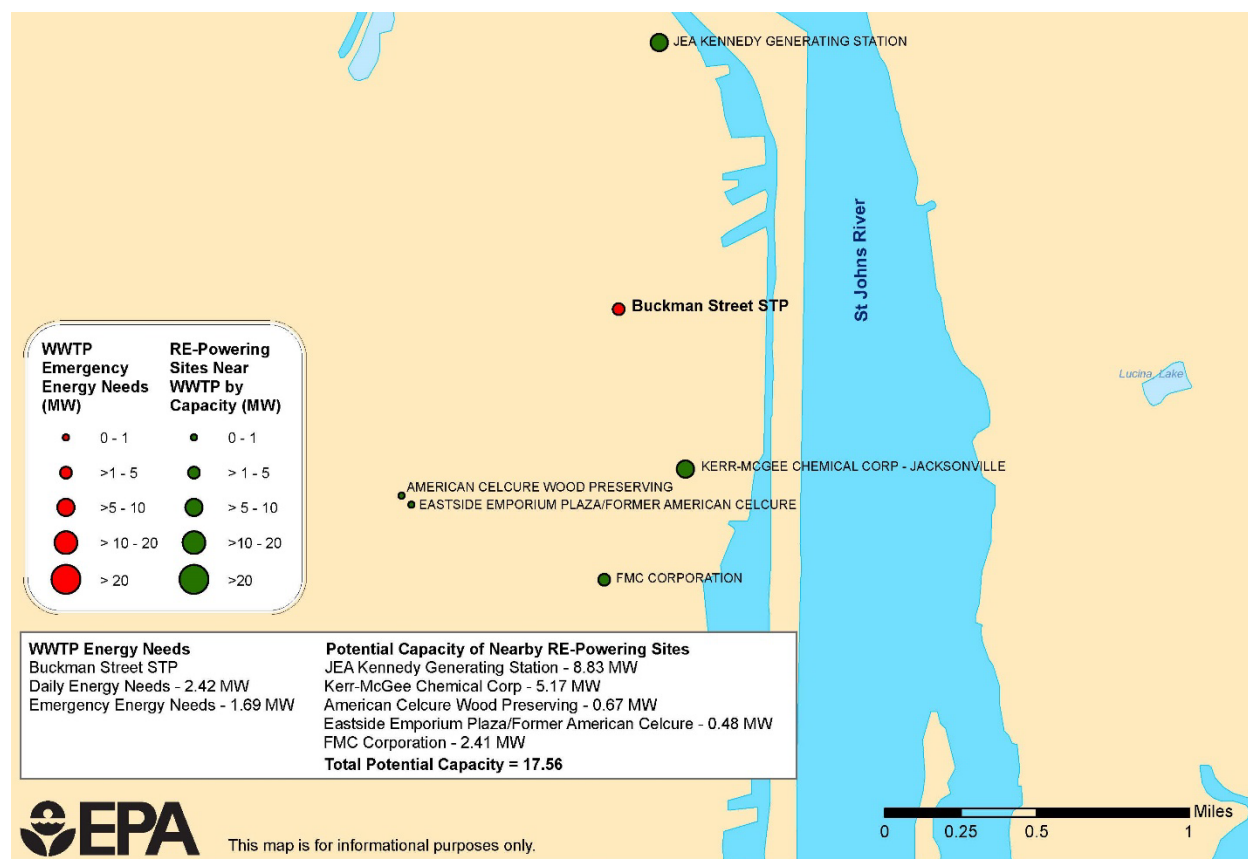


Southeast

The Southeast region, comprises Alabama, Florida, Georgia, North Carolina, South Carolina, Virginia and the District of Columbia. This region has a high frequency of tropical storms, inland and coastal flooding. Based on the vulnerability analysis, 25 WWTPs in the Southeast region are rated at least 4 (“high threat/moderate probability” or “moderate threat/high probability”) for tropical storms, 20 for coastal flooding, and 23 for inland flooding.

Across the region, there are 55 RE-Powering sites with economically competitive solar or wind capacity that is sufficient to support the emergency energy needs of nearby WWTPs. In addition to meeting the emergency energy needs, there are 40 RE-Powering sites with economically competitive solar and/or wind capacity that is sufficient to support the daily energy needs of nearby WWTPs. Figure 8 illustrates the spatial proximity of the sites and favorable screening results.

Figure 8: Comparison of WWTPs by Energy Need and nearby Potential RE-Powering Sites by Capacity in the Jacksonville, Florida Area

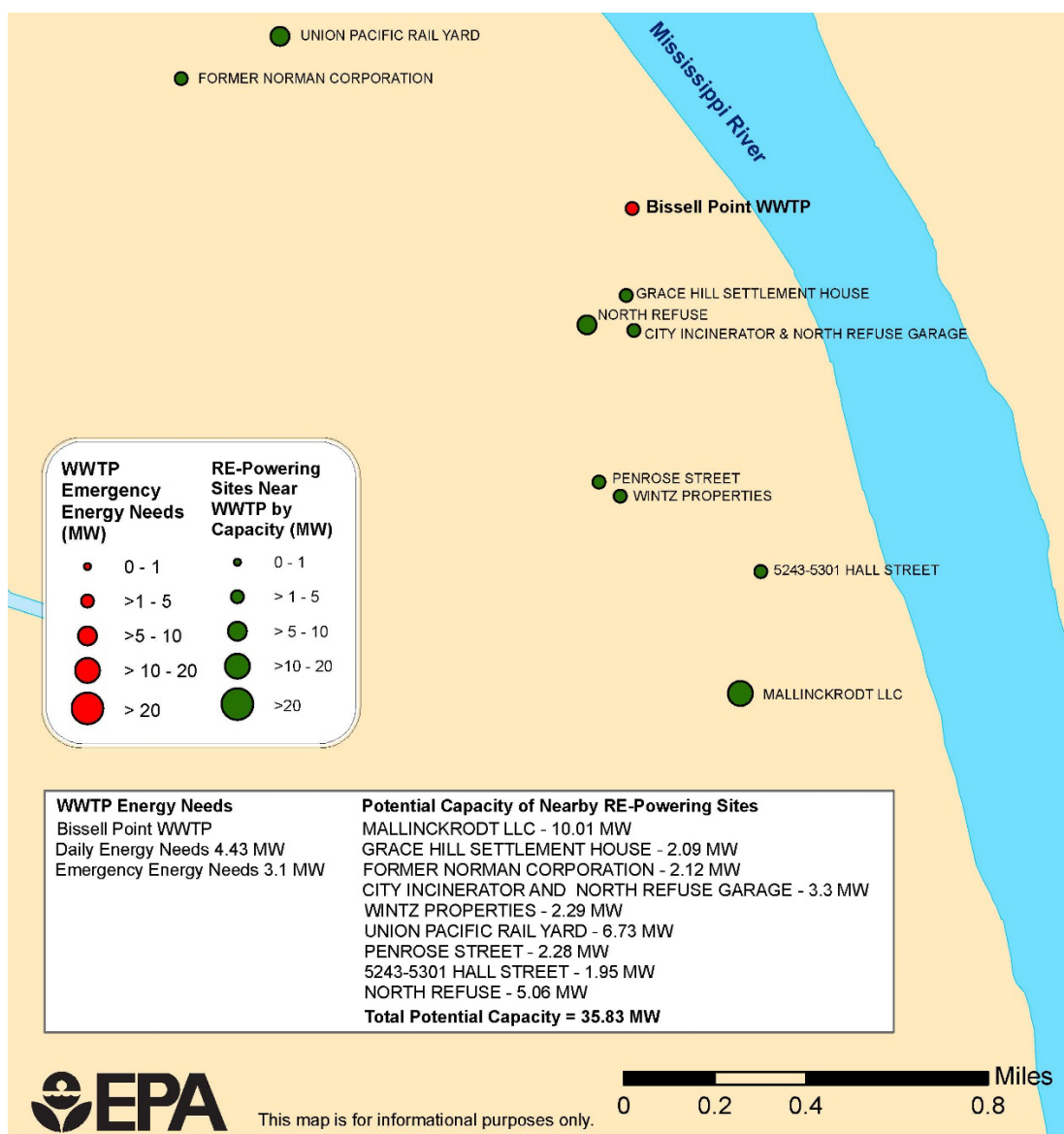


Ohio Valley (Central)

The Ohio Valley region comprises Illinois, Indiana, Kentucky, Missouri, Ohio, Tennessee, and West Virginia. This region has a high risk for damaging tornados. Based on the vulnerability analysis, seven WWTPs in the Ohio Valley region have a high threat and high probability for tornados.

Across the region, there are 32 RE-Powering sites with economically competitive solar or wind capacity that is sufficient to support the emergency energy needs of nearby WWTPs. In addition to meeting the emergency energy needs, there are 30 RE-Powering sites with economically competitive solar and/or wind capacity that is sufficient to support the daily energy needs of nearby WWTPs. Figure 9 illustrates the spatial proximity of the sites and favorable screening results.

Figure 9: Comparison of WWTPs by Energy Need and nearby Potential RE-Powering Sites by Capacity in the St. Louis, Missouri Area

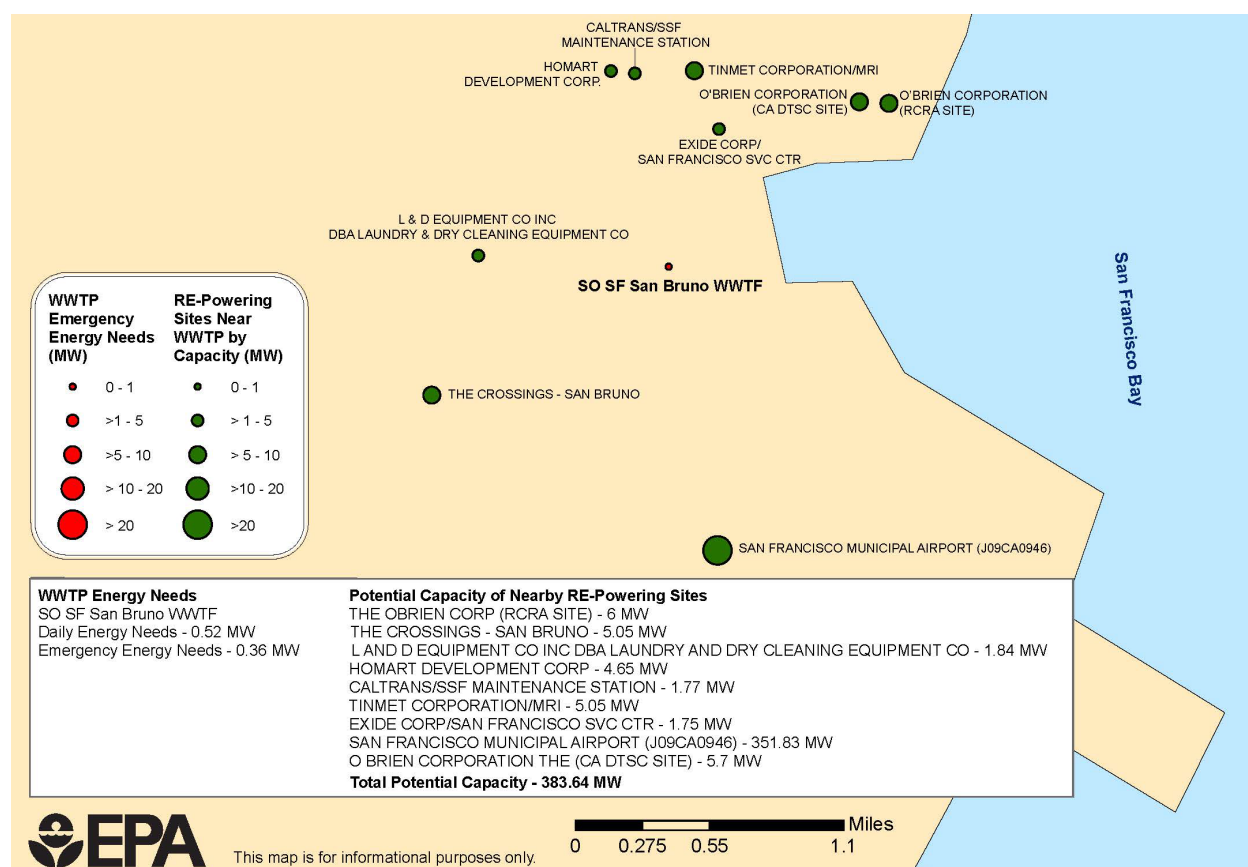


West

The West region comprises California and Nevada and has a high potential for outages caused by earthquake or coastal flooding. Based on the vulnerability analysis, 25 WWTPs in the Southeast region are rated at least 4 (“high threat/moderate probability” or “moderate threat/high probability”) WWTP in the West region have a high threat and high probability for earthquakes and 19 WWTP for coastal flooding.

Across the region, there are 88 RE-Powering sites with economically competitive solar or wind capacity that is sufficient to support the emergency energy needs of nearby WWTPs. In addition to meeting the emergency energy needs, there are 87 RE-Powering sites with economically competitive solar and/or wind capacity that is sufficient to support the daily energy needs of nearby WWTPs. Figure 10 illustrates the spatial proximity of the sites and favorable screening results.

Figure 10: Comparison of WWTPs by Energy Need and nearby Potential RE-Powering Sites by Capacity in the San Francisco Bay, California Area



Discussion

The methodology described herein is intended to provide an initial screening of sites and infrastructure to support broader strategic analyses—that is, to identify locations for further exploration of RE-Powering opportunities. More in-depth and site-specific analyses would be required to understand the feasibility of using a RE-Powering site to support the energy needs of critical infrastructure at any one specific location.

In developing the methodology, assumptions were necessary to support a national-level analysis of the likelihood that certain events might happen and that those events might have a catastrophic impact on the grid. Assumptions also helped match RE-Powering site energy outputs to critical infrastructure needs. The 1-mile proximity was decided as a reasonable distance between the RE-Powering site and the WWTP that would facilitate the ability to microgrid the sites and manage or reduce costs associated with building transmission lines. Other distances between RE-Powering sites and WWTPs could be considered and explored as well. Assumptions and associated uncertainties are described in the detailed information about the approach for developing the screening criteria ([Appendix A](#)).

The data collected for this analysis all have some limitations ([Appendix C](#) provides a list of data sources). For example, the WWTPs were extracted from the CWNS, which contains data from a voluntary survey. As such, the data may not represent all the possible WWTPs in a region and the accuracy of the data cannot be guaranteed; however, available data was sufficient to apply the described methodology and analyze the results. EPA visually verified the locations of select CWNS WWTPs by looking at the locations on a mapping application to reduce some uncertainties.

In addition to its methodological assumptions, the analysis recognizes that extreme weather events and natural hazards that can cause long-term power outages for critical infrastructure also create vulnerabilities for renewable energy installations. A balance must be found between being able to provide power in a time of need and protecting a renewable energy installation. This can limit the capacity of a renewable energy installation to meet critical infrastructure needs during an emergency. Two reports provide some insight into best practices for solar systems subjected to hurricane and other severe weather events:

- *Solar Under Storm: Select Best Practices for Resilient Ground Mount PV Systems with Hurricane Exposure*⁶ by the Rocky Mountain Institute studies similarities of solar PV systems that both failed and survived during the 2017 hurricane season. The report discusses how incorporating the best available engineering, design, delivery, and operational practices can increase the reliability and survival rates from extreme wind loading.
- The U.S. Department of Energy's (DOE's) *Solar Photovoltaic Systems in Hurricanes and Other Severe Weather*⁷ highlights how field examinations of damaged solar PV systems have revealed important design, construction, and operational factors that greatly influence a system's

⁶ *Solar Under Storm: Select Best Practices for Resilient Ground Mount PV Systems with Hurricane Exposure*, accessed at https://www.rmi.org/wp-content/uploads/2018/06/Islands_SolarUnderStorm_Report_digitalJune122018.pdf

⁷ *Solar Photovoltaic Systems in Hurricanes and Other Severe Weather*, accessed at https://www.energy.gov/sites/prod/files/2018/08/f55/pv_severe_weather.pdf.

survivability from a severe weather event. These events demonstrate the importance of good operational and maintenance practices as a survivability factor, in addition to pre- and post-storm measures that can greatly minimize equipment damage and recovery time.

State, local, and utility-level standards and codes can also affect and possibly limit the installation of renewable energy installations in areas prone to flooding, earthquakes, and extreme storms. Most of the information related to safety standards for renewable energy installations is administered at the state, local, or even utility levels, as conditions vary widely across the United States.

For example, at the state level, Florida [requires](#) that rooftop solar systems meet the Florida Building Code for permitting solar panels. The Code requires that solar panels (components and cladding) meet imposed wind loads. California's [codes](#) for constructing solar PV systems in seismic zones are required to include, "[c]alculations [that] demonstrate that the solar PV panels and associated supporting members are designed to resist earthquake loads." Because standards and codes vary at state and local levels, it was not possible to efficiently integrate these considerations into a methodology with national coverage.

It should also be noted that economic competitiveness is not static. State and regional policies can change, resulting in new economic conditions and opportunities.

Application to Other Types of Infrastructure

The methodology was intentionally designed to allow for replication to incorporate other types of critical infrastructure (e.g., hospitals, schools, emergency centers, cell towers, fire stations, natural gas distribution centers, and others).

To replicate the analysis, datasets (including spatial data) for additional critical infrastructure types would be required, such as emergency power needs and information about the utility servicing the critical infrastructure. This information could then be joined to information compiled for vulnerability screening, LCOE data, and site-associated power generation capacity. In general, the steps for replicating the analysis for other types of infrastructure are as follows:

1. Compile hazard vulnerability data for the hazards of interest. (See Appendix C for data sources).
2. Determine level of risk and probability to be evaluated for analysis. Screen RE-Powering sites by overlaying them with hazard vulnerability areas.
3. Identify critical infrastructure assets that are within a predetermined distance from RE-Powering sites identified in step 2. These will be the critical infrastructure assets of interest.
4. Gather information and assign economic competitiveness of renewable energy to the critical infrastructure assets of interest at the desired scale.
5. Assess the emergency power needs of the remaining infrastructure assets using data sources and methods applicable to the infrastructure type. Then compare the emergency power needs of the infrastructure assets with the renewable energy capacity of associated RE-Powering sites.

Conclusion

The use of RE-Powering sites provides numerous potential benefits to communities, including returning idle lands to productive use, providing electricity cost savings and stable electricity costs through Power Purchase Agreements, and reducing greenhouse gas emissions. In addition, RE-Powering sites present opportunities for powering critical infrastructure, including immediately after sudden power outages (for example, as a result of a tropical storm). Renewable energy in combination with a decentralized electricity grid can make communities more resilient. This approach could provide power when antiquated grids fail or, at least, could allow for isolation of specific facilities against outages, including those associated with natural disasters and other events.

Critical infrastructure is vital to protecting human health and the environment. In the case of WWTPs, a system failure during a prolonged power outage can result in waste being released to [rivers](#), streams, [lakes](#), or groundwater, thus impacting ecosystems as well as public health. This analysis demonstrates how it may be possible to match the need to maintain critical WWTP infrastructure with potential RE-Powering sites that are economically beneficial, in areas with high vulnerability to natural disasters. In addition, the methodology, as outlined in this analysis, could be applied to other types of critical infrastructure besides WWTPs. Consistent with the results of this analysis, it is believed that RE-Powering sites could likely meet the specific energy demands of other types of critical infrastructure as well.

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Appendix A: Approach for Developing Screening Criteria

The following appendix describes the approaches used for developing the screening criteria used in the methodology for evaluating the potential for RE-Powering Sites to Support Critical Infrastructure.

Vulnerability Screening

The analysis used vulnerability screening to identify sites that are in areas at high risk for potential extended power outages due to the following types of hazards:

- Hurricanes/tropical storms
- Tornadoes
- Coastal flooding, including effects of storm surge and sea level rise (SLR)
- Inland flooding
- Earthquakes
- Wildfires

Future analyses may also consider vulnerability to power outage from winter storms (a key hazard for the electricity grid), depending on the availability of data supporting geospatial vulnerability analysis of this type of hazard.

For the vulnerability screening, a one-mile buffer was assigned to each RE-Powering site and each buffer area was screened to characterize hazard-specific vulnerability using the generalized risk-based framework described herein. For areas subject to multiple threats (e.g., coastal areas subject to flooding and hurricanes), the highest vulnerability category was used to categorize the overall vulnerability for the area. Hazard-specific and overall relative vulnerability categories were recorded for each area to allow for hazard-specific analysis and to show the nature of the critical vulnerability associated with each area.⁸

Threat Categories

The proposed vulnerability screening approach follows a generalized risk-based framework. Each type of event identified represents a “hazard.” For purposes of this approach, the potential that a hazard will cause a power outage is defined as the “threat,” and “vulnerability” is characterized by combining a measure of relative threat and relative probability of exposure to the threat.

To establish the draft vulnerability screening framework, the following steps were completed for each type of hazard:

- Characterized the nature of the hazard
- Identified existing scales and research associated with each type of hazard and developed threat thresholds corresponding to relatively high, moderate, and low threats of power outage

⁸ The intent of vulnerability screening is to identify critical infrastructure—rather than potential RE-Powering sites—that could be vulnerable to more frequent and intense weather events. The approach combines elements of the proximity and vulnerability screening to define a vulnerability layer of “areas within a mile of a RE-Powering site” that could be vulnerable to extreme weather events. The approach is “infrastructure-neutral” in that it allows for overlaying different types of infrastructure on this vulnerability layer (including, in this case, WWTPs) without the need for reanalysis. The overlaid critical infrastructure is linked to the underlying vulnerability rating and associated with proximal RE-Powering site(s). See the “Replicating the Analysis” section document below for further discussion.

- Identified data sources that are available for national geospatial analysis and could be used to categorize the probability of an area being exposed to a hazard at different threat levels.

Table 1 summarizes the resulting threat scales and levels (thresholds) associated with each type of hazard. The tables in Appendix C identify the rationale and information sources used to develop the proposed threat categorization approach.

Table 1. Proposed Threat Scales and Thresholds for Vulnerability Screening

| Category | Hazard(s) | Threat scales | Threat Thresholds |
|----------------------------------|----------------------------|---|---|
| Hurricane/ Tropical Storm | High winds, inundation | Saffir-Simpson hurricane wind scale and related tropical cyclone categories | High: SSWS \geq 74 mph Moderate: 39 mph \leq SSWS $<$ 74 mph Low: SSWS $<$ 39 mph |
| Tornadoes | High winds | Enhanced Fujita Tornado Scale | High: EF \geq 3 Moderate: 1 \leq EF $<$ 3 Low: EF = 0 |
| Coastal Flooding ⁹ | Inundation, wave energy | Depth of projected inundation based on SFHA designation, predicted SLR, and storm surge potential | High: DW ₁₀₀ \geq 3 feet Moderate: 0 feet \leq DW ₁₀₀ $<$ 3 feet Low: Outside 100-year flood zone and DW ₅₀₀ \geq 0 feet |
| Inland Flooding | Inundation | Depth of inundation based on SFHA designation | High: DW ₁₀₀ \geq 3 feet Moderate: 0 feet \leq DW ₁₀₀ $<$ 3 feet Low: Outside 100-year flood zone and DW ₅₀₀ \geq 0 feet |
| Earthquakes | Ground acceleration | Seismic fragility curves | High: PGA \geq 0.48 Moderate: 0.16 \leq PGA $<$ 0.48 Low: PGA $<$ 0.16 |
| Wildfire | Fire | WHP classification scale (for the conterminous U.S.) | High: WHP = high or very high Moderate: WHP = moderate Low: WHP = low or very low |

Acronyms used in Table 1: DW₁₀₀ = water depth, 100-year storm; DW₅₀₀ = water depth, 500-year storm; EF = Enhanced Fujita Tornado Damage Scale value; SSWS = sustained surface wind speed; PGA = Peak ground acceleration value (as fraction of gravitational acceleration); SFHA = Special Flood Hazard Area, as designated under the National Flood Insurance Program; SLR = sea level rise; WHP = Wildfire Hazard Potential

Probability Categories

The following relative probability categories were developed to support the relative vulnerability analysis:

- High probability: \geq 1% annual probability of occurrence (\leq 100-year return period)
- Moderate probability: \geq 0.2% annual probability of occurrence (\leq 500-year return period)
- Low probability: $<$ 0.2% annual probability of occurrence

⁹ Coastal flooding has additional considerations based on storm surge and sea level rise dynamics (see the Coastal Flooding Hazard Category in Table 1).

These levels mirror the approach used by the National Flood Insurance Program (NFIP) for characterizing flood risk. The approach facilitates the use of flood risk data without the need for further statistical analysis.

Vulnerability Categories

Table 2 describes proposed vulnerability categories developed based on combinations of threat and probability categories.

Table 2. Proposed Vulnerability Categories

| Category | Threat-Probability Combination | Hazard-specific Combinations | | |
|----------|--|------------------------------|--|----------------------|
| | | Hazard | Threat Value | Annual Probability |
| 5 | High threat/ high probability | Hurricane/Trop. Storm | SSWS \geq 74 mph | $p \geq 1\%$ |
| | | Tornado | EF \geq 3 | |
| | | Coastal flooding* | DW ₁₀₀ \geq 3 feet | |
| | | Inland flooding | DW ₁₀₀ \geq 3 feet | |
| | | Earthquake | PGA \geq 0.48 | |
| | | Wildfire | WHP \geq high | |
| 4 | High threat/ moderate probability | Hurricane/Trop. Storm | SSWS \geq 74 mph | $0.2\% \leq p < 1\%$ |
| | | Tornado | EF \geq 3 | |
| | | Coastal flooding* | DW ₁₀₀ \geq 3 feet | |
| | | Inland flooding | DW ₁₀₀ \geq 3 feet | |
| | | Earthquake | PGA \geq 0.48 | |
| | | Wildfire | WHP \geq high | |
| | Moderate threat/ high probability | Hurricane/Trop. storm | $39 \text{ mph} \leq \text{SSWS} < 74 \text{ mph}$ | $p \geq 1\%$ |
| | | Tornado | $1 \leq \text{EF} < 3$ | |
| | | Coastal flooding* | $0 \text{ feet} \leq \text{DW}_{100} < 3 \text{ feet}$ | |
| | | Inland flooding | $0 \text{ feet} \leq \text{DW}_{100} < 3 \text{ feet}$ | |
| | | Earthquake | $0.16 \leq \text{PGA} < 0.48$ | |
| | | Wildfire | WHP = moderate | |
| 3 | Moderate threat/ moderate probability | Hurricane/Trop. storm | $39 \text{ mph} \leq \text{SSWS} < 74 \text{ mph}$ | $0.2\% \leq p < 1\%$ |
| | | Tornado | $1 \leq \text{EF} < 3$ | |
| | | Coastal flooding* | $0 \text{ feet} \leq \text{DW}_{100} < 3 \text{ feet}$ | |
| | | Inland flooding | $0 \text{ feet} \leq \text{DW}_{100} < 3 \text{ feet}$ | |
| | | Earthquake | $0.16 \leq \text{PGA} < 0.48$ | |
| | | Wildfire | WHP = moderate | |
| 2 | Moderate-to-high threat/ low probability | Hurricane/Trop. storm | SSWS \geq 39 mph | $p < 0.2\%$ |
| | | Tornado | EF \geq 1 | |
| | | Coastal flooding* | DW ₁₀₀ \geq 0 feet | |
| | | Inland flooding | DW ₁₀₀ \geq 0 feet | |
| | | Earthquake | PGA \geq 0.16 | |
| | | Wildfire | WHP \geq moderate | |
| | Low threat/ moderate-to-high probability | Hurricane/Trop. storm | SSWS $<$ 39 mph | $p \geq 0.2\%$ |

| Category | Threat-Probability Combination | Hazard-specific Combinations | | |
|----------|--------------------------------|------------------------------|--|--------------------|
| | | Hazard | Threat Value | Annual Probability |
| | | Tornado | EF = 0 | |
| | | Coastal flooding* | Outside 100-yr flood zone and DW ₅₀₀ ≥ 0 feet | |
| | | Inland flooding | Outside 100-yr flood zone and DW ₅₀₀ ≥ 0 feet | |
| | | Earthquake | PGA < 0.16 | |
| | | Wildfire | WHP < moderate | |
| 1 | Low threat/ low probability | Hurricane/Trop. storm | SSWS < 39 mph | p < 0.2% |
| | | Tornado | EF = 0 | |
| | | Coastal flooding* | Outside 100-yr flood zone and DW ₅₀₀ ≥ 0 feet | |
| | | Inland flooding | Outside 100-yr flood zone and DW ₅₀₀ ≥ 0 feet | |
| | | Earthquake | PGA < 0.16 | |
| | | Wildfire | WHP < moderate | |

* For coastal flooding, threat-probability levels are based on existing SFHA flood zone designation, which represents analysis of flood frequency potential under existing coastal conditions, and judgement regarding how the flood frequency designation may change by the year 2050 under the 0.5-MED and 1.0-MED SLR scenarios described in NOAA (2017)

Acronyms used in Table 2: DW₁₀₀ = water depth (feet), 100-year storm; DW₅₀₀ = water depth (feet), 500-year storm; EF = Enhanced Fugita Tornado Damage Scale value; SSWS = sustained surface wind speed; PGA = Peak ground acceleration value (fraction of gravitational acceleration); SFHA = Special Flood Hazard Area, as designated under the National Flood Insurance Program; SLR = sea level rise (feet); WHP = Wildfire Hazard Potential

The same natural hazards that can cause long-term power outages for critical infrastructure could also affect the renewable energy installations located nearby. This screening-level analysis is intended to identify contaminated sites with renewable energy potential that are located near vulnerable critical infrastructure and could be incorporated into a broader energy resilience strategy. More in-depth analysis would be required prior to proceeding with a renewable energy installation in areas prone to flooding, earthquakes, and storm paths (see the *Limitations* section above).

Proximity Screening

The proximity screening step identified RE-Powering sites within one mile of a WWTP, using the generated site boundary¹⁰ for each site from the RE-Powering Mapper dataset. In many cases, this resulted in one-to-many relationships, where multiple RE-Powering sites were identified in proximity to a WWTP facility. This also resulted in some instances where multiple WWTPs were located in proximity

¹⁰ This is the site boundary created by using a radius that generates a site boundary equivalent to the area of the site as recorded - see [Data Documentation for Mapping and Screening Criteria for Renewable Energy Generation Potential on EPA and State Tracked Sites RE-Powering America's Land Initiative](#) for more detail on the RE-Powering Mapper Dataset.

to a single RE-Powering site. The latter situation would likely be more prevalent if additional types of critical infrastructure (e.g., drinking water treatment facilities, hospitals) were included in the analysis.

This approach does not account for existing transmission infrastructure and potential physical or other barriers that could affect the effective distance between a RE-Powering site and a critical infrastructure asset. This analysis is intended to provide an initial screening in support of broader strategic analyses. More in-depth analysis would be required prior to understand the feasibility of using a RE-Powering site to support the energy needs of critical infrastructure.

The set of sites resulting from proximity screening were further screened based on potential economic competitiveness (economic screening) and capacity to serve emergency power needs of associated critical infrastructure (needs screening), as described in the subsequent sections. Five renewable energy technologies were considered in these subsequent screening analyses:¹¹

- Utility-scale PV solar
- Large-scale PV solar
- Utility-scale wind
- Large-scale wind
- 1–2 turbine wind

Economic Screening

Economic screening was used to further screen sites identified in the proximity screening based on whether the cost of developing renewable energy installations at these sites would be competitive with other electricity-generating technologies. To assess competitiveness, the analysis compared electricity pricing data for utility service and pricing territories where potential sites are located to regional LCOE estimates developed by the U.S. Energy Information Agency (EIA). Sites were ranked in terms of economic viability based on this comparison, as outlined later in this section.

The electric utility serving the area for each site was identified using Electric Retail Service Territories data from the Department of Homeland Security's [Homeland Infrastructure Foundation-Level Data](#). Where available, electricity pricing data were collected for each utility associated with a site using the EIA 2016 Utility Bundled Retail Sales – Industrial data files.¹² Where pricing data were not readily available for an area, the analysis used state-level pricing data for the industrial end-user category from the EIA Electric Power Annual report.¹³

EIA estimates LCOE for technologies entering service in any year from 2018 to 2051 using its National Energy Modeling System (NEMS).¹⁴ LCOE is an estimate of the cost of building and operating a generating plant over its financial life and is used to evaluate the relative competitiveness of different generating technologies. EIA develops LCOE estimates for 22 different NEMS regions and provides

¹¹ See [Data Documentation for Mapping and Screening Criteria for Renewable Energy Generation Potential on EPA and State Tracked Sites RE-Powering America's Land Initiative](#) for more information on the renewable energy technology and screening requirements.

¹² Electric Sales, Revenue, and Average Price with Data for 2016 ; Release date: November 6, 2017; Table T8. Accessed January 23, 2018 at https://www.eia.gov/electricity/sales_revenue_price/.

¹³ Electric Power Annual, with Data for 2016; Release date: December 7, 2017; Table 2.10, Average Price of Electricity to Ultimate Customers by End-Use Sector, by State, 2016 and 2015. Accessed January 23, 2018 at https://www.eia.gov/electricity/annual/html/epa_02_10.html.

¹⁴ NEMS is a computer-based model developed by EIA to project the production, imports, conversion, consumption, and prices of energy through 2030.

detailed information at a national scale for the years 2019, 2022 and 2040.¹⁵ EIA recommends using LCOE estimates for the year 2022 for evaluating the potential economic competitiveness of new installations to account for lead time and licensing requirements.

Annual regional LCOE estimates are not publicly available but were provided on request by EIA to support this analysis. Each site included in the dataset was associated with a NEMS region. LCOE estimates were collected for each site for conventional wind and solar PV fixed-tilt technologies. Consistent with EIA’s recommended approach, LCOE estimates for the year 2022 were used for economic screening.

Pricing information was compared to LCOE estimates for each site to provide an initial screening and classify the competitiveness of developing renewable energy installations: very competitive, competitive, possibly competitive, or not competitive using the outlined. LCOE estimates are based on assumptions regarding capital costs, fixed and variable operations and maintenance costs, financing costs, and utilization rate. All of these factors are affected by location-specific factors and can vary regionally and over time, contributing to uncertainty in LCOE estimates. Ranges were used in the economic screening criteria to account for these sources of uncertainty.

| Ranking | Basis |
|----------------------|--|
| Very competitive | LCOE < 90% of current electricity price |
| Competitive | 90% current electricity price ≤ LCOE ≤ 110% current electricity price |
| Possibly competitive | 110% current electricity price < LCOE ≤ 120% current electricity price |
| Not competitive | LCOE > 120% of current electricity price |

Incentives can also affect the competitiveness of a potential renewable energy installation on contaminated lands. Such incentives include net metering, renewable portfolio standards, solar set-asides, solar and/or wind multipliers, distributed generation, and special considerations for development on contaminated lands. Quantitative and qualitative data were collected for states and regions where sites in the dataset are located and could be considered in future, refined analyses of renewable energy competitiveness. Incentives would tend to make renewable energy facilities more competitive. The ranges outlined in the ranking table (e.g., in the criteria for the “possibly competitive” category) were used in this screening-level analysis to account for the potential effects of incentives.

From a state and local perspective, the benefits of developing renewable energy installations extend beyond revenue generation. They could include the benefits of infrastructure resiliency, or avoiding costs associated with power outages. These outage-related costs could include short- and long-term environmental contamination, deleterious effects to human health, business shutdowns and work stoppages, and higher costs associated with restarting operations. While the benefits of resiliency and reliability can be difficult to quantify, it is important to qualitatively consider these attributes when evaluating the use of renewable energy to support critical infrastructure.

¹⁵ EIA (2017). Levelized Cost and Levelized Avoided Cost of New Generation Resources in the Annual Energy Outlook 2017. Accessed January 23, 2018 at https://www.eia.gov/outlooks/aeo/electricity_generation.php.

Needs Screening

Needs screening was used to further screen sites identified in the proximity screening based on whether the potential power that the RE-Powering sites could produce would match the energy needs of the associated WWTP. The screening considered that the RE-Powering installation would likely not need to supply the full operating power for the facility, but instead only a level capable of powering critical operations protective of human health, safety, and the environment through an emergency situation.

WWTP data from the EPA CWNS was used to categorize facilities according to major WWTP types identified in the Water Research Foundation and the Electric Power Research Institute study, *Electricity Use and Management in the Municipal Water Supply and Wastewater Industries* (WRF/EPRI, 2013).¹⁶ Information regarding average electric energy intensities, including adjustment factors for levels of treatment and average flow, were used to estimate the electric energy intensity for each WWTP included in the dataset. Emergency power requirements were estimated based on electric energy intensity, average daily flow rate data from the CWNS, and an adjustment factor for emergency power load.

The steps completed are as follows:

1. The CWNS field PRES_FACILITY_TYPE was used to identify facilities that are treatment plants (WWTPs) versus facilities that are collection systems only. Facilities identified as collection systems only were removed from further consideration. The remaining dataset included 156 WWTPs.
2. The CWNS fields PRES_EFFLUENT_TREATMENT_LEVEL and DISCHARGE_METHOD were used to categorize WWTPs in terms of treatment types listed in Table 5-5 of the WRF/EPRI (2013) document, under the following categorization:

Table 1. Treatment Type Categories Based on CWNS Data

| Effluent Treatment Level (PRES_EFFLUENT_TREATMENT_LEVEL) | Discharge Method ¹ (DISCHARGE_METHOD) | Treatment Type Category |
|---|--|--|
| Secondary | <ul style="list-style-type: none"> ◆ Outfall to Surface Waters ◆ Ocean Discharge ◆ CSO Discharge | Secondary |
| Secondary | <ul style="list-style-type: none"> ◆ Reuse: Groundwater Recharge ◆ Spray Irrigation ◆ Evaporation | Secondary + No Discharge |
| Advanced Treatment | <ul style="list-style-type: none"> ◆ Outfall to Surface Waters ◆ Ocean Discharge | Greater Than Secondary |
| Advanced Treatment | <ul style="list-style-type: none"> ◆ Reuse: Groundwater Recharge ◆ Spray Irrigation ◆ Evaporation | Greater Than Secondary + No Discharge |
| Advanced Treatment | <ul style="list-style-type: none"> ◆ Reuse: Industrial ◆ Reuse: Irrigation | Greater Than Secondary + Pumping Reuse Water |

¹⁶ WRF/EPRI (2013). *Electricity Use and Management in the Municipal Water Supply and Wastewater Industries*. Palo Alto, CA: Electric Power Research Institute. Accessed September 29, 2017 at <http://www.waterrf.org/Pages/Projects.aspx?PID=4454>

¹ Only combinations of effluent treatment level and discharge method in the current dataset are included in this table. The crosswalk can be generalized for all CWNS data if necessary.

- Electric energy intensities for WWTPs in the dataset were estimated based on treatment-type category and average daily flow using the following categorization, which was derived from the electric energy intensities in Table 5-5 of the WRF/EPRI (2013) study (adjusted for flow rate using Table 5-4 of the study).

Table 2. Estimated Average Electric Energy Intensities by Treatment Type and Flow Rate

| Treatment Type Category | Electric Energy Intensity (kWh/MG) by Average Daily Flow Rates (MG) | | | | | |
|--|---|---------|----------|----------|-----------|-------|
| | <5 | 5 - <10 | 10 - <20 | 20 - <50 | 50 - <100 | >100 |
| Secondary | 2,151 | 1,291 | 1,133 | 1,041 | 978 | 957 |
| Secondary + No Discharge | 2,366 | 1,420 | 1,246 | 1,145 | 1,076 | 1,053 |
| Greater Than Secondary | 2,809 | 1,785 | 1,638 | 1,527 | 1,439 | 1,428 |
| Greater Than Secondary + No Discharge | 3,090 | 1,964 | 1,802 | 1,680 | 1,583 | 1,571 |
| Greater Than Secondary + Pumping Reuse Water | 4,089 | 3,065 | 2,918 | 2,807 | 2,719 | 2,708 |

- Electric energy needs for each WWTP in the dataset were calculated based on electric energy intensity and average daily flow reported in CWNS. Emergency power load was estimated as 70% of average electric energy needs based on Figure 5-2 from the WRF/EPRI (2013) study and the simplifying assumption that emergency power is required for all pumping and treatment unit processes except biosolids processing.

Tables 3 and 4 present a summary of the breakdown of treatment type and flow rate categories for the 156 facilities in the preliminary dataset using the proposed approach.

Table 3. Breakdown of Facilities by Treatment Type Category Using CWNS Data

| Effluent Treatment Level | Discharge Method | Facility Count | Treatment Type Category |
|--------------------------|-----------------------------|----------------|--|
| Secondary | Outfall To Surface Waters | 58 | Secondary |
| | Ocean Discharge | 9 | |
| | CSO Discharge | 1 | |
| Secondary | Reuse: Groundwater Recharge | 1 | Secondary + No Discharge |
| | Spray Irrigation | 1 | |
| | Evaporation | 1 | |
| Advanced Treatment | Outfall To Surface Waters | 58 | Greater Than Secondary |
| | Ocean Discharge | 3 | |
| Advanced Treatment | Reuse: Groundwater Recharge | 1 | Greater Than Secondary + No Discharge |
| | Spray Irrigation | 5 | |
| | Evaporation | 1 | |
| Advanced Treatment | Reuse: Industrial | 1 | Greater Than Secondary + Pumping Reuse Water |
| | Reuse: Irrigation | 3 | |

| Effluent Treatment Level | Discharge Method | Facility Count | Treatment Type Category |
|------------------------------------|-------------------------------|----------------|-------------------------|
| Not "Treatment Plant" ¹ | Discharge To Another Facility | 12 | N/A |
| | CSO Discharge | 1 | |
| Total | | 156 | |

¹ One facility in the dataset was identified as a "Treatment Plant" with "Raw Water" effluent treatment level. Upon further review, it was determined that the facility is a collection system without treatment, not a WWTP.

Table 4. Breakdown of Facilities by Treatment Type Category and Average Daily Flow

| Treatment Type Category | Flow Rate Category | | Facility Count |
|---|--------------------|----------|----------------|
| | Min Flow | Max Flow | |
| Secondary | 0 | <5 | 28 |
| | 5 | <10 | 9 |
| | 10 | <20 | 14 |
| | 20 | <50 | 5 |
| | 50 | <100 | 5 |
| | 100 | no max | 7 |
| Subtotal – Secondary | | | 68 |
| Secondary + No discharge | 0 | <5 | 2 |
| | 5 | <10 | 0 |
| | 10 | <20 | 0 |
| | 20 | <50 | 0 |
| | 50 | <100 | 1 |
| | 100 | no max | 0 |
| Subtotal – Secondary + No discharge | | | 3 |
| Greater Than Secondary | 0 | <5 | 21 |
| | 5 | <10 | 10 |
| | 10 | <20 | 7 |
| | 20 | <50 | 9 |
| | 50 | <100 | 6 |
| | 100 | no max | 8 |
| Subtotal – Greater Than Secondary | | | 61 |
| Greater Than Secondary + No Discharge | 0 | <5 | 6 |
| | 5 | <10 | 1 |
| | 10 | <20 | 0 |
| | 20 | <50 | 0 |
| | 50 | <100 | 0 |
| | 100 | no max | 0 |
| Subtotal – Greater Than Secondary + No Discharge | | | 7 |
| Greater Than Secondary + Pumping Reuse Water | 0 | <5 | 1 |
| | 5 | <10 | 2 |
| | 10 | <20 | 1 |
| | 20 | <50 | 0 |
| | 50 | <100 | 0 |
| | 100 | no max | 0 |
| Subtotal – Greater Than Secondary + Pumping Reuse Water | | | 4 |
| Not treatment | | | 13 |
| Total | | | 156 |

Appendix B: Rationale and Information Sources for Proposed Threat Categorization

| Hazard category: Hurricane/Tropical Storm | |
|--|---|
| Nature of hazard | High winds, inundation |
| Threat scales | Saffir-Simpson hurricane wind scale and related tropical cyclone categories (NWS 2016). |
| Threat thresholds | High: SSWS \geq 74 mph (categorized hurricane) Moderate: 39 mph \leq SSWS < 74 mph (categorized tropical storm) Low: SSWS < 39 mph |
| Threshold basis | Likelihood of outage based on NWS tropical cyclone categorization; high threat corresponds to any categorized hurricane (on the Saffir-Simpson scale); moderate threat corresponds to categorized tropical storm (NWS 2016). |
| Data sources for assessing probability | International Best Track Archive for Climate Stewardship (IBTrACS) (NCEI 2017): the IBTrACS project works directly with all the Regional Specialized Meteorological Centers and other international centers and individuals to create a global best track dataset, merging storm information from multiple centers into one product and archiving the data for public use. |
| Periods used as basis for probability assessment | <ul style="list-style-type: none"> • Probability based on more recent data for 1980–2015: <ul style="list-style-type: none"> ○ The National Climate Assessment notes a substantial increase in most measures of Atlantic hurricane activity since the early 1980s, though ability to assess longer-term trends is limited by the quality of available data prior to the satellite era (early 1970s) (USGCRP 2014) ○ National Centers for Environmental Information (NCEI) (2017) includes data through 2015 • Supplemental analysis of probability based on historical record from 1851 to 2015 (NCEI 2017) |
| Description of approach | <ul style="list-style-type: none"> • Calculate annual probability of hurricane (high threat event) and tropical storm (moderate threat event) for counties intersecting the site boundary plus 1-mile buffer using 1980–2015 period; all areas identified will fall into “high probability” category (\geq 1 event/35 years \rightarrow $p \geq$ 1%) • For counties not identified with high probability events, calculate annual probability of hurricane and tropical storm for counties intersecting the site boundary plus 1-mile buffer using 1851-2015 period • Select the highest vulnerability category associated with threat-probability combination(s) |

Acronyms:

SSWS = sustained surface wind speed

Hazard category: Tornado

| | |
|--|--|
| Nature of hazard | High winds |
| Threat scales | Enhanced Fujita Tornado Scale (NWS 2016b) |
| Threat thresholds | High: EF \geq 3 Moderate: $1 \leq$ EF < 3 Low: EF = 0 |
| Threshold basis | Likelihood of energy sector impacts as described in Colorado Energy Office (2016), p. 190; descriptions of typical damage based on Enhanced Fujita Tornado Scale (NOAA 2016) |
| Data sources for assessing probability | Tornado tracks by F-scale as recorded in the NOAA/NCEI Storm Events Database (NCEI 2016) and made available for geospatial analysis through SVRGIS (NWS 2016c). |
| Periods used as basis for probability assessment | <ul style="list-style-type: none"> • Probability based on more recent data from 1976–2015: <ul style="list-style-type: none"> ○ The National Climate Assessment states that trends in the intensity and frequency of tornadoes are uncertain and are being studied intensively (USGCRP 2014) ○ Tornado intensity classification has been more reliable since the advent and adoption of the Fujita scale in the mid-1970s (Edwards et al. 2013; Grazulis et al. 1993) ○ NCEI (2016) includes data through 2015 • Supplemental analysis of probability based on historical record from 1950 to 2015 (NCEI 2016) |
| Description of approach | <ul style="list-style-type: none"> • Calculate annual probability of tornado of strength EF3 or higher (high threat event) and tornado of EF1 or EF2 (moderate threat event) for counties intersecting the site boundary plus 1 mile buffer using 1976-2015 period; all areas identified will fall into “high probability” category (\geq 1 event/39 years \rightarrow p \geq 1%) • For counties not identified based on the 1976–2015 period, calculate annual probability of tornado of strength EF3 or higher and tornado of EF1 or EF2 for counties intersecting the site boundary plus 1 mile buffer using 1950-2015 period; these areas will also fall into high probability category (\geq 1 event/65 years \rightarrow p \geq 1%) • Select the highest vulnerability category associated with threat-probability combination(s) |

Acronyms:

EF = Enhanced Fugita Tornado Damage Scale value

Hazard category: Coastal Flooding

| | |
|--|--|
| Nature of hazard | Inundation, wave energy |
| Threat scales | Depth of projected inundation based on NFIP SFHA designation, predicted sea level rise, and storm surge potential |
| Threat thresholds ¹ | High: $DW_{100} \geq 3$ feet Moderate: $0 \text{ feet} \leq DW_{100} < 3$ feet Low: Outside of 100-year flood zone and $DW_{500} \geq 0$ feet |
| Threshold basis | Breakpoint between “shallow” flooding and deeper baseline flood elevation (BFE) used by NFIP (FEMA 2016) for classifying areas within 100-year floodplain |
| Data sources for assessing probability | <ul style="list-style-type: none"> • NFIP FIRM data, to establish baseline inundation hazard based on SFHA designation • NOAA et al. (2017), to establish SLR value at grid stations along U.S. coasts, based on intermediate scenario, year 2050 • NOAA Digital Coast data (NOAA 2016), to establish SLR inundation extent based on projected SLR level • SLOSH model data, to establish current storm surge hazard (NHC 2016) |
| Periods used as basis for probability assessment | <p>Varies by site-specific factors/embedded in dataset:</p> <ul style="list-style-type: none"> • Flood return period designations are based on detailed modeling that account for data availability and changes (e.g., land cover) affecting flood frequency (FEMA 2017) • Probabilistic SLR projections based on alternative future greenhouse-gas emission and associated ocean-atmosphere warming scenarios are used to derive regional RSL responses on a 1-degree grid covering the coastlines of the U.S. and its territories (NOAA 2017). • The SLOSH model estimates storm surge heights based on historical, hypothetical, or predicted hurricanes accounting for specific locales’ shoreline configurations, water depths, and other physical features (NHC 2016) |
| Description of approach | <ul style="list-style-type: none"> • Establish “coastal” sites: <ul style="list-style-type: none"> ○ Identify sites within one mile of predicted potential inundation of coastal areas resulting from a projected 1–6-foot rise in sea level above current Mean Higher High Water (MHHW) conditions based on NOAA Digital Coast model (NOAA 2016) • Establish parameters for buffer area: <ul style="list-style-type: none"> ○ Identify whether any area in the buffer is projected to be inundated due to SLR under each of the following scenarios from NOAA (2017): <ul style="list-style-type: none"> ▪ Intermediate-Low GMSL scenario, median value (“0.5-MED”) ▪ Intermediate GMSL scenario, median value (“1.0-MED”) ○ Select highest risk SFHA designation within site buffer ○ Identify whether SLOSH model identifies impacts to any area in buffer based on Cat 1 hurricane and, if so, maximum MOM for buffer • Establish threat level and probability based on SFHA designation and predicted SLR: <ul style="list-style-type: none"> ○ High threat-high probability: <ul style="list-style-type: none"> ▪ SFHA designation = “V”, “VE”, “AE Coastal”, or “AE” with a BFE of ≥ 3 feet ▪ “AE” designation with a BFE of < 3 feet and predicted inundation by SLR under 1.0-MED scenario |

| Nature of hazard | Inundation, wave energy |
|------------------|---|
| | <ul style="list-style-type: none"> ▪ Other “A” designation and predicted inundation by SLR under 1.0-MED scenario SLR ▪ Predicted inundation by SLR based on the 0.5-MED scenario (regardless of current SFHA designation/status) ○ Moderate threat-high probability: <ul style="list-style-type: none"> ▪ “AE” designation and a BFE of < 3 feet and no SLR inundation predicted ▪ Other “A” designation and no SLR inundation predicted ▪ Shaded “X” designation (formerly Zone B) and predicted SLR inundation under 1.0-MED scenario ○ Low threat-moderate probability: <ul style="list-style-type: none"> ▪ Shaded “X” designation (formerly Zone B) and no SLR predicted ▪ Not currently in NFIP-designated flood zone and predicted inundation by SLR under 1.0-MED scenario ● Establish threat level and probability for storm surge (for buffers not assigned high threat based on above): <ul style="list-style-type: none"> ○ Threat level: <ul style="list-style-type: none"> ▪ High threat for MOM ≥ 3 feet ▪ Medium threat for 0 feet < MOM < 3 feet ▪ Low threat for MOM < 0 feet ○ Probability based on probability of Cat 1 hurricane (from Hurricane/ Tropical Storm hazard method) ● Select the highest vulnerability category associated with threat-probability combination(s) |

Notes:

¹ Threat levels are based on existing SFHA flood zone designation, which represents analysis of flood frequency potential under existing coastal conditions, and judgement regarding how the flood frequency designation may change by the year 2050 under the 0.5-MED and 1.0-MED SLR scenarios described in NOAA (2017).

Acronyms:

- DW₁₀₀ = water depth (feet), 100-year storm
- DW₅₀₀ = water depth (feet), 500-year storm
- FIRM = Flood Insurance Rate Map
- GMSL = Global mean sea level
- MOM = maximum of maximum envelope of water
- NFIP = National Flood Insurance Program
- SFHA = Special Flood Hazard Area
- SLOSH = Sea, Lake and Overland Surges from Hurricanes
- SLR = sea level rise

Hazard category: Inland Flooding

| | |
|--|--|
| Nature of hazard | Inundation |
| Threat scales | Depth of inundation based on NFIP SFHA designation |
| Threat thresholds* | High: $D_w \geq 3$ feet Moderate: $0 \text{ feet} \leq D_w < 3$ feet Low: Outside of 100-year flood zone and $DW_{500} \geq 0$ feet |
| Threshold basis | Breakpoint between “shallow” flooding and deeper BFE used by NFIP (FEMA 2016) for classifying areas within 100-year floodplain |
| Data sources for assessing probability | NFIP FIRM data, to establish baseline inundation hazard based on SFHA designation |
| Periods used as basis for probability assessment | Varies by site-specific factors/embedded in dataset: <ul style="list-style-type: none"> Flood return period designations are based on detailed modeling that account for data availability and changes (e.g., land cover) affecting flood frequency (FEMA 2017) |
| Description of approach | <ul style="list-style-type: none"> Select highest risk SFHA designation within site boundary plus 1-mile buffer Establish highest threat level (based on highest risk SFHA designation): <ul style="list-style-type: none"> High threat: “AE” designation with a BFE of ≥ 3 feet Moderate threat: <ul style="list-style-type: none"> “AE” designation with a BFE of < 3 feet Other “A” designation Low threat: shaded “X” designation (formerly Zone B) Select the highest vulnerability category associated with threat-probability combination(s), where 100-year flood corresponds to 1% annual probability and 500-year flood corresponds to 0.2% annual probability |

***Note:** An inundation depth of one foot is more likely to represent a threat of power outage than the depth of zero feet used in the screening analysis (see Boggess et al., 2014, for a discussion of standard practice for elevating substation equipment). However, depth of inundation information is not consistently available for NFIP-designated flood zones. The 0-foot inundation depth included in the screening method reflects this limitation. Some areas within the intersection between a designated flood zone and the site plus 1-mile buffer area may be exposed to a higher threat than other areas.

Acronyms:

- BFE = base flood elevation
- DW_{100} = water depth (feet), 100-year storm
- DW_{500} = water depth (feet), 500-year storm
- FIRM = Flood Insurance Rate Map
- NFIP = National Flood Insurance Program
- SFHA = Special Flood Hazard Area

Hazard category: Earthquake

| | |
|---|---|
| Nature of hazard | Ground acceleration |
| Threat scales | Seismic fragility curves (FEMA 2015) |
| Threat thresholds | High: PGA \geq 0.48 Moderate: $0.16 \leq$ PGA $<$ 0.48 Low: PGA $<$ 0.16 |
| Threshold basis | \geq 75% probability of extensive damage (high threat), \leq 25% moderate damage (low threat), and all others moderate threat; approximate unweighted averages of ranges for critical power network infrastructure, FEMA (2015), Figs. 8.46–8.57 |
| Data sources for assessing probability | Seismic Ground Motion Hazards with 10% Probability (DHS 2012): GIS shapefiles for 10% PGA probability in 50 years (conterminous United States only) |
| Period used as basis for probability assessment | 1700-2006: <ul style="list-style-type: none"> • USGS (2008) documents the 2008 update of the U.S. National Seismic Hazard Maps used as the basis for DHS (2012) • Seismic probabilistic hazard is modeled based on seismicity-derived hazard sources, earthquakes on faults, and ground shaking resulting from these earthquakes using a catalogue of approximately 3,350 earthquakes from 1700 through 2006 (USGS 2008) |
| Description of approach | <ul style="list-style-type: none"> • Identify highest threat level based on PGA value within site boundary plus 1-mile buffer • Select the highest vulnerability category associated with threat-probability combination(s), where all threats are associated with a 0.2% (moderate) probability (10%/50 years) |

Acronyms:

PGA = Peak ground acceleration value (as fraction of gravitational acceleration)

Hazard category: Wildfire

| | |
|--|---|
| Nature of hazard | Fire |
| Threat scales | Wildfire Hazard Potential (WHP) classification scale developed for the conterminous U.S. (Dillon et al. 2015; USFS 2014) |
| Threat thresholds | High: WHP = high or very high Moderate: WHP = moderate Low: WHP = low or very low |
| Threshold basis | U.S. Forest Service (USFS) classification of WHP considering large and small wildfire burn potential and resistance to control using fire suppression resources |
| Data sources for assessing probability | Spatial dataset of probabilistic wildfire risk components for the conterminous United States: National burn probability data generated for the conterminous United States using a geospatial Fire Simulation (FSim) system developed by the U.S. Forest Service Missoula Fire Sciences Laboratory to estimate probabilistic components of wildfire risk (Short et al. 2016) |

| | |
|---|--|
| Nature of hazard | Fire |
| Period used as basis for probability assessment | 1970-2008: <ul style="list-style-type: none"> • Burn probabilities represented in Short et al. (2016) were developed based wildfire and weather data for the period from circa 1970 to 2008 (Finney et al. 2011) |
| Description of approach | <ul style="list-style-type: none"> • Identify all combinations of WHP classification and annual burn probability intersecting the site boundary plus 1-mile buffer • Select the highest vulnerability category associated with the threat-probability combination(s) |

References for Hurricane/Tropical Storm:

NCEI (2017) International Best Track Archive for Climate Stewardship. Accessed February 23, 2017, at <https://www.ncdc.noaa.gov/ibtracs/index.php?name=ibtracs-data>.

NWS (2016). Tropical Cyclone Classification. U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Weather Service. Accessed January 5, 2017, at <http://www.nws.noaa.gov/os/hurricane/resources/TropicalCyclones11.pdf>.

USGCRP (2014). Climate Change Impacts in the United States: The Third National Climate Assessment. U.S. Global Change Research Program, 841 pp. Accessed February 16, 2017 at <http://nca2014.globalchange.gov/>.

References for Tornado:

Colorado Energy Office (2016). Colorado Energy Assurance Emergency Plan. Accessed December 29, 2016 at <https://www.colorado.gov/pacific/energyoffice/energy-assurance-plan>.

Edwards, R., J.G. LaDue, J.T. Feree, K. Scharfenberg, C. Maier, and W.L. Coulbourne (2013). Tornado Intensity Estimation, Past, Present, and Future. *Bulletin of the American Meteorological Society*, May 2013, 641-653. Accessed February 17, 2017 at <http://journals.ametsoc.org/doi/full/10.1175/BAMS-D-11-00006.1>.

Grazulis, T. P., J. T. Schaefer, and R.F. Abbey Jr. (1993). Advances in tornado climatology, hazards, and risk assessment since Tornado Symposium II. *The Tornado: Its Structure, Dynamics, Prediction, and Hazard, Geophys. Monogr.*, No. 79, Amer. Geophys. Union, 409-426.

NWS (2016b). Fujita Tornado Damage Scale. National Weather Service, Storm Prediction Center. Accessed December 29, 2016 at www.spc.noaa.gov/faq/tornado/f-scale.html.

NCEI (2016). Storm Events Database. Accessed January 9, 2017 at <https://www.ncdc.noaa.gov/stormevents/>.

NWS (2016c). Storm Prediction Center Severe Weather GIS (SVRGIS). Data available at <http://www.spc.noaa.gov/gis/svrgis/>.

References for Coastal Flooding:

- FEMA (2016). National Flood Insurance Program: Flood Hazard Mapping. Federal Emergency Management Agency. Accessed January 9, 2017 at <https://www.fema.gov/national-flood-insurance-program-flood-hazard-mapping> .
- FEMA (2017). Numerical Models Meeting the Minimum Requirements of the National Flood Insurance Program. Accessed February at <https://www.fema.gov/numerical-models-meeting-minimum-requirements-national-flood-insurance-program>.
- NHC (2016). Sea, Lake, and Overland Surges from Hurricanes (SLOSH). National Oceanic and Atmospheric Administration, National Hurricane Center. Accessed January 11, 2017 at <http://www.nhc.noaa.gov/surge/slosh.php>.
- NOAA (2016). Sea Level Rise Viewer. National Oceanic and Atmospheric Administration, Office for Coastal Management. Accessed January 11, 2017 at <https://coast.noaa.gov/digitalcoast/tools/slr>.
- NOAA, USGS, EPA, and Rutgers University (2017). Global and Regional Sea Level Rise Scenarios for the United States. NOAA Technical Report NOS CO-OPS 083. Accessed February 17, 2017 at https://tidesandcurrents.noaa.gov/publications/techrpt83_Global_and_Regional_SLR_Scenarios_for_the_US_final.pdf.

References for Inland Flooding:

- Bogges, J.M., G.W. Becker, and M.K. Mitchell (2014). Storm & Flood Hardening of Electrical Substations. IEEE 2014 T&D Conference Paper 14TD0564. Accessed February 17, 2017 at <http://www.ieee-pes.org/presentations/td2014/td2014p-000564.pdf>.
- FEMA (2016). National Flood Insurance Program: Flood Hazard Mapping. Federal Emergency Management Agency. Accessed January 9, 2017 at <https://www.fema.gov/national-flood-insurance-program-flood-hazard-mapping> .
- FEMA (2017). Numerical Models Meeting the Minimum Requirements of the National Flood Insurance Program. Accessed February at <https://www.fema.gov/numerical-models-meeting-minimum-requirements-national-flood-insurance-program>.

References for Earthquake:

- DHS (2012). Seismic Ground Motion Hazards with 10 Percent Probability. Department of Homeland Security (DHS), Homeland Infrastructure Foundation-Level Data (HIFLD). Accessed February 15, 2017 at https://hifld-dhs-gii.opendata.arcgis.com/datasets/a6802a1025074246bce2dd96863cb93a_0.
- FEMA (2015). Multi-hazard Loss Estimation Methodology, Earthquake Model, Hazus®–MH 2.1, Technical Manual. U.S. Department of Homeland Security, Federal Emergency Management Agency.
- USGS (2008). Documentation for the 2008 Update of the United States National Seismic Hazard Maps: U.S. Geological Survey Open-File Report 2008–1128, 61 p. Accessed February 15, 2017 at <https://pubs.usgs.gov/of/2008/1128/>.

References for Wildfire:

- Dillon, G.K., J. Menakis and F. Fay (2015). Wildland Fire Potential: A Tool for Assessing Wildfire Risk and Fuels Management Needs. USDA Forest Service Proceedings RMRS-P-73. Accessed January 12, 2017 at <https://www.treesearch.fs.fed.us/pubs/49429>.
- Finney, M.A., C.W. McHugh, I.C. Grenfell, K. L. Riley, and K. C. Short (2011). A simulation of probabilistic wildfire risk components for the continental United States. USDA Forest Service/UNL Faculty Publications. Paper 249. Accessed .February 14, 2017 at <https://www.treesearch.fs.fed.us/pubs/39312>
- Short, K.C., M.A. Finney, J.H. Scott, J.W. Gilbertson-Day, and I.C. Grenfell (2016). Spatial dataset of probabilistic wildfire risk components for the conterminous United States. Data available at <https://www.fs.usda.gov/rds/archive/Product/RDS-2016-0034>.
- USFS (2014). Classified 2014 WHP: GIS Data and Maps. U.S. Forest Service; Fire, Fuel, and Smoke Science Program. Accessed January 12, 2017 at <https://www.firelab.org/document/classified-2014-whp-gis-data-and-maps>.

Appendix C: Datasets Used for the Analysis

The following datasets were used in the geospatial analyses.

| Screening Type | Element | Dataset | Description | Restrictions | Source |
|----------------|----------------------------|--|---|--------------|--------|
| Initial | Contaminated Lands | RE-Powering Mapper | Provides detailed information for over 80,000 sites screened for renewable energy potential. | None | EPA |
| Proximity | Critical Infrastructure | Waste Water Treatment Plants | EPA's Clean Watersheds Needs Survey (CWNS) is an assessment of capital investment needed nationwide for publicly-owned wastewater collection and treatment facilities to meet the water quality goals of the Clean Water Act. Data in the CWNS are organized by "facility." For CWNS, the term facility used to describe a wastewater, stormwater management, and/or decentralized wastewater management project and location needed to address a water quality or a water quality related-public health problem. Only "Wastewater" facilities were evaluated for this study. | None | EPA |
| Vulnerability | Current and Future Hazards | Flood Hazard Zones | These zones are used by the federal Emergency Management Agency (FEMA) to designate the Special Flood Hazard Area (SFHA) and for insurance rating purposes. These data are the flood hazard areas that are or will be depicted on the Flood Insurance Rate Map (FIRM). | None | FEMA |
| | | Historical Tornado Tracks | This layer from NOAA's Storm Prediction Center Severe Weather GIS shows tornado tracks in the United States, Puerto Rico, and the U.S. Virgin Islands, from 1950 to 2015. | None | NOAA |
| | | Historical Tropical Storm Tracks | This Historical North Atlantic and Eastern North Pacific Tropical Cyclone Tracks file contains the 6-hour center locations and intensities for all subtropical depressions and storms, extratropical storms, tropical lows, waves, disturbances, depressions and storms, and all hurricanes, from 1851 through 2008. | None | NOAA |
| | | Sea Level Rise | This dataset depicts potential sea level rise and its associated impacts on the nation's coastal areas. The data depict the potential inundation of coastal areas resulting from a projected 1- to 6-foot rise in sea level above current Mean Higher High Water (MHHW) conditions. | None | NOAA |

| Screening Type | Element | Dataset | Description | Restrictions | Source |
|----------------|----------------------------|--|--|--------------|-----------------------------------|
| Vulnerability | Current and Future Hazards | Global and Regional Sea Level Rise Scenarios for the United States | This report highlights the linkages between scenario-based and probabilistic projections of future sea levels for coastal-risk planning, management of long-lived critical infrastructure, mission readiness, and other purposes. The probabilistic projections discussed in this report recognize the inherent dependency (conditionality) of future global mean sea level (GMSL) rise. GMSL rise and associated RSL change are quantified from the year 2000 through the year 2200 (on a decadal basis to 2100 and with lower temporal frequency between 2100 and 2200). | None | NOAA |
| | | Sea, Lake and Overland Surges from Hurricanes (SLOSH) model | This model is used to assist in a range of planning processes, risk assessment studies, and operational decision-making. Tens of thousands of climatology-based hypothetical tropical cyclones are simulated in each SLOSH basin (or grid), and the potential storm surges are calculated. Storm surge composites – Maximum Envelopes of Water (MEOWs) and Maximum of MEOWs (MOMs) – are created to assess and visualize storm surge risk under varying conditions. | | |
| | | Seismic Ground Motion Hazards with 10 Percent Probability | These data represent seismic hazard in the United States. The data represent a model showing the probability that ground motion will reach a certain level. This map layer shows peak horizontal ground acceleration (the fastest measured change in speed, for a particle at ground level that is moving horizontally due to an earthquake) with a 10% probability of exceedance in 50 years. Values are given in %g, where g is acceleration due to gravity, or 9.8 meters/second ² . | None | USGS ¹⁷ |
| | | Probabilistic Wildfire Risk Components | National burn probability estimates probabilistic components of wildfire risk. It is a national-scale assessment of wildfire risk and offers a consistent means of understanding and comparing threats to valued resources and predicting and prioritizing investments in management activities that mitigate those risks. | None | USDA Forest Service ¹⁸ |

¹⁷ Data from Homeland Security Infrastructure Program (HSIP) data. Source listed in table is the primary source referenced by HSIP.

¹⁸ Short, Karen C.; Finney, Mark A.; Scott, Joe H.; Gilbertson-Day, Julie W.; Grenfell, Isaac C. 2016. Spatial dataset of probabilistic wildfire risk components for the conterminous United States. Fort Collins, CO: Forest Service Research Data Archive. <https://doi.org/10.2737/RDS-2016-0034>.

| Screening Type | Element | Dataset | Description | Restrictions | Source |
|----------------------|--------------------------------------|---|---|--------------|---|
| Vulnerability | Current and Future Hazards | Wildfire Hazard Potential | This dataset is a raster geospatial product that can help to inform evaluations of wildfire risk or prioritization of fuels management needs across very large spatial scales (millions of acres). This dataset is not an explicit map of wildfire threat or risk, but when paired with spatial data depicting highly valued resources and assets such as structures or powerlines, it can approximate relative wildfire risk to those specific resources and assets. | None | USDA Forest Service ¹⁹ |
| Economic | Utility Service Territories | Electric Retail Service Territories | The Electric Retail Service Territories represent the service areas of companies who report retail and/or commercial electricity sales to the EIA 861 Form. These companies may be investor-owned utilities, electric cooperatives, municipalities, power marketers, etc. | None | EIA and Homeland Infrastructure Foundation – Level Data (HIFLD) |
| | Levelized Cost of Electricity (LCOE) | Regional LCOE values | Levelized cost of electricity (LCOE) is often cited as a convenient summary measure of the overall competitiveness of different generating technologies. It represents the per-kilowatt-hour cost (in discounted real dollars) of building and operating a generating plant over an assumed financial life and duty cycle. | Unsure | EIA (special request) |

¹⁹ Fire Modeling Institute, USDA Forest Service, Rocky Mountain, 20141222, Wildfire Hazard Potential (WHP) for the conterminous United States (270-m GRID), v2014 classified [whp2014_cls].

Appendix D: Additional Summary of Findings Tables

Table 1. Number, Location and Size of Potential RE-Powering Sites

| State/Territory (by Weather Region) | All Potential RE Powering Sites | | Potential RE Powering Sites Capable of Supporting at Least Large Scale Power Generation | | |
|---|---------------------------------|------------------|---|------------------|--------------------------|
| | Number of Sites | Total Acreage | Number of Sites | Total Acreage | Total Est. Capacity (MW) |
| Northeast | | | | | |
| Connecticut | 611 | 15,682 | 234 | 12,843 | 2,134 |
| Delaware | 173 | 18,122 | 115 | 17,272 | 2,895 |
| Maine | 490 | 25,280 | 110 | 23,353 | 3,542 |
| Maryland | 337 | 103,348 | 148 | 92,459 | 14,692 |
| Massachusetts | 2,507 | 83,434 | 837 | 76,867 | 12,823 |
| New Hampshire | 297 | 9,850 | 60 | 8,354 | 1,362 |
| New Jersey | 11,068 | 472,372 | 2,442 | 401,485 | 58,669 |
| New York | 3,254 | 525,776 | 1,484 | 508,749 | 81,380 |
| Pennsylvania | 6,992 | 1,087,964 | 1,995 | 424,607 | 42,424 |
| Rhode Island | 341 | 4,824 | 61 | 4,227 | 743 |
| Vermont | 307 | 4,165 | 89 | 3,119 | 560 |
| Subtotal | 26,377 | 2,350,818 | 7,575 | 1,573,335 | 221,223 |
| Southeast and Caribbean Islands | | | | | |
| Alabama | 407 | 215,009 | 144 | 203,585 | 33,832 |
| District of Columbia | 75 | 79,011 | 17 | 78,966 | 13,161 |
| Florida | 1,582 | 1,399,480 | 345 | 1,366,453 | 227,850 |
| Georgia | 551 | 590,670 | 249 | 571,674 | 95,289 |
| North Carolina | 953 | 513,335 | 213 | 501,460 | 83,473 |
| Puerto Rico | 208 | 34,369 | 61 | 16,443 | 2,764 |
| South Carolina | 428 | 877,024 | 152 | 868,758 | 143,565 |
| U.S. Virgin Islands | 1 | 6 | 0 | 0 | 0 |
| Virginia | 5,839 | 380,761 | 1,005 | 320,252 | 52,698 |
| Subtotal | 10,044 | 4,089,665 | 2,186 | 3,927,591 | 652,631 |
| Upper Midwest (East North Central) | | | | | |
| Iowa | 879 | 48,468 | 199 | 48,019 | 8,127 |
| Michigan | 2,786 | 454,169 | 726 | 448,531 | 72,786 |
| Minnesota | 904 | 877,684 | 333 | 877,028 | 146,107 |
| Wisconsin | 985 | 351,740 | 382 | 350,871 | 57,954 |
| Subtotal | 5,554 | 1,732,062 | 1,640 | 1,724,450 | 284,974 |
| Ohio Valley (Central) | | | | | |
| Illinois | 6,985 | 297,760 | 1,997 | 290,308 | 48,608 |
| Indiana | 993 | 180,144 | 311 | 178,049 | 29,598 |
| Kentucky | 358 | 268,130 | 148 | 266,832 | 44,412 |
| Missouri | 1,600 | 712,718 | 304 | 711,375 | 117,926 |
| Ohio | 1,222 | 142,683 | 495 | 118,791 | 9,264 |
| Tennessee | 367 | 292,981 | 123 | 287,371 | 47,166 |
| West Virginia | 2,445 | 81,196 | 590 | 39,585 | 6,615 |
| Subtotal | 13,970 | 1,975,612 | 3,968 | 1,892,311 | 303,589 |
| South | | | | | |
| Arkansas | 292 | 227,723 | 116 | 223,701 | 36,376 |
| Kansas | 799 | 217,231 | 257 | 216,636 | 35,619 |
| Louisiana | 501 | 281,811 | 199 | 278,462 | 46,353 |

| State/Territory (by Weather Region) | All Potential RE Powering Sites | | Potential RE Powering Sites Capable of Supporting at Least Large Scale Power Generation | | |
|---|---------------------------------|-------------------|---|-------------------|--------------------------|
| | Number of Sites | Total Acreage | Number of Sites | Total Acreage | Total Est. Capacity (MW) |
| Mississippi | 348 | 23,126 | 100 | 14,256 | 2,377 |
| Oklahoma | 559 | 205,175 | 246 | 204,532 | 34,218 |
| Texas | 2,429 | 815,375 | 1,128 | 807,461 | 132,013 |
| Subtotal | 4,928 | 1,770,441 | 2,046 | 1,745,046 | 286,956 |
| Northern Rockies and Plains (West North Central) | | | | | |
| Montana | 318 | 533,754 | 89 | 515,884 | 85,941 |
| Nebraska | 268 | 129,496 | 125 | 129,088 | 21,349 |
| North Dakota | 142 | 42,007 | 26 | 41,930 | 6,937 |
| South Dakota | 212 | 12,503 | 36 | 12,275 | 1,994 |
| Wyoming | 56 | 17,072 | 26 | 17,036 | 2,847 |
| Subtotal | 996 | 734,832 | 302 | 716,213 | 119,068 |
| Southwest | | | | | |
| Arizona | 588 | 4,335,816 | 145 | 4,331,340 | 721,905 |
| Colorado | 718 | 622,315 | 163 | 617,688 | 102,993 |
| New Mexico | 202 | 3,338,101 | 95 | 3,337,761 | 556,328 |
| Utah | 276 | 956,761 | 92 | 955,711 | 159,288 |
| Subtotal | 1,784 | 9,252,992 | 495 | 9,242,500 | 1,540,513 |
| Northwest | | | | | |
| Idaho | 284 | 4,127,741 | 103 | 4,116,079 | 686,031 |
| Oregon | 5,171 | 1,342,570 | 816 | 1,236,914 | 205,162 |
| Washington | 560 | 2,414,976 | 63 | 2,173,272 | 361,136 |
| Subtotal | 6,015 | 7,885,287 | 982 | 7,526,265 | 1,252,329 |
| West | | | | | |
| California | 10,138 | 10,836,458 | 2,486 | 10,783,495 | 1,788,037 |
| Nevada | 440 | 1,002,799 | 116 | 1,000,822 | 166,820 |
| Subtotal | 10,578 | 11,839,257 | 2,602 | 11,784,317 | 1,954,858 |
| Other | | | | | |
| Alaska | 176 | 1,364,639 | 2 | 348 | 24 |
| Hawaii | 1,245 | 789,556 | 501 | 762,451 | 125,351 |
| Subtotal | 1,421 | 2,154,195 | 503 | 762,799 | 125,375 |
| Total | 81,667 | 43,785,162 | 22,299 | 40,894,827 | 6,741,516 |

Table 2. Summary of Potential for RE-Powering Sites to Meet Emergency Power Needs of WWTPs Identified Based on Proximity, Vulnerability, and Needs Screening Criteria

| State | WWTPs | Average Daily Flow | | | Emergency Power Needs | | | RE Capacity Available | | | RE Capacity to Emergency Power Ratio | |
|----------------------|------------|--------------------|--------------|------------|-----------------------|-------------|------------|-----------------------|--------------|------------|--------------------------------------|------------|
| | | Total | Max | Min | Total | Max | Min | Total | Max | Min | Max | Min |
| Arizona | 3 | 9.3 | 6.8 | 1.1 | 0.6 | 0.4 | 0.1 | 9.3 | 6.8 | 1.1 | >1,000 | >1,000 |
| Arkansas | 1 | 2.2 | 2.2 | 2.2 | 0.1 | 0.1 | 0.1 | 2.2 | 2.2 | 2.2 | 13.7 | 13.7 |
| California | 23 | 671.8 | 325.0 | 0.9 | 22.7 | 9.1 | 0.1 | 671.8 | 325.0 | 0.9 | >1,000 | 0.5 |
| Connecticut | 1 | 8.0 | 8.0 | 8.0 | 0.4 | 0.4 | 0.4 | 8.0 | 8.0 | 8.0 | 57.7 | 57.7 |
| District of Columbia | 1 | 370.0 | 370.0 | 370.0 | 15.4 | 15.4 | 15.4 | 370.0 | 370.0 | 370.0 | 1.5 | 1.5 |
| Florida | 11 | 103.6 | 50.5 | 0.1 | 6.1 | 2.1 | 0.0 | 103.6 | 50.5 | 0.1 | >1,000 | 0.3 |
| Georgia | 2 | 7.1 | 5.6 | 1.5 | 0.3 | 0.2 | 0.1 | 7.1 | 5.6 | 1.5 | 926.2 | 3.0 |
| Illinois | 4 | 844.7 | 812.0 | 1.7 | 35.4 | 33.8 | 0.1 | 844.7 | 812.0 | 1.7 | 485.8 | 46.6 |
| Maine | 1 | 2.0 | 2.0 | 2.0 | 0.1 | 0.1 | 0.1 | 2.0 | 2.0 | 2.0 | 14.5 | 14.5 |
| Maryland | 1 | 1.4 | 1.4 | 1.4 | 0.1 | 0.1 | 0.1 | 1.4 | 1.4 | 1.4 | >1,000 | >1,000 |
| Massachusetts | 17 | 107.6 | 25.8 | 0.9 | 4.6 | 0.8 | 0.1 | 107.6 | 25.8 | 0.9 | >1,000 | 5.8 |
| Michigan | 2 | 741.5 | 660.5 | 81.0 | 30.9 | 27.5 | 3.4 | 741.5 | 660.5 | 81.0 | >1,000 | 11.9 |
| Mississippi | 3 | 14.9 | 6.0 | 3.8 | 0.7 | 0.3 | 0.2 | 14.9 | 6.0 | 3.8 | 870.3 | 15.8 |
| Missouri | 3 | 239.0 | 114.0 | 14.0 | 6.8 | 3.2 | 0.5 | 239.0 | 114.0 | 14.0 | 40.3 | 3.0 |
| New Hampshire | 1 | 12.0 | 12.0 | 12.0 | 0.4 | 0.4 | 0.4 | 12.0 | 12.0 | 12.0 | 3.8 | 3.8 |
| New Jersey | 7 | 286.6 | 177.6 | 0.2 | 11.3 | 7.4 | 0.0 | 286.6 | 177.6 | 0.2 | >1,000 | 0.9 |
| New York | 7 | 615.7 | 271.3 | 1.0 | 21.7 | 7.6 | 0.1 | 615.7 | 271.3 | 1.0 | 205.8 | 2.2 |
| North Carolina | 3 | 19.0 | 14.0 | 1.9 | 1.1 | 0.7 | 0.2 | 19.0 | 14.0 | 1.9 | 44.2 | 1.9 |
| Pennsylvania | 3 | 201.6 | 196.7 | 1.7 | 5.9 | 5.5 | 0.1 | 201.6 | 196.7 | 1.7 | >1,000 | 3.3 |
| Texas | 8 | 321.4 | 152.0 | 1.2 | 13.9 | 6.3 | 0.1 | 321.4 | 152.0 | 1.2 | >1,000 | 3.5 |
| Vermont | 1 | 1.7 | 1.7 | 1.7 | 0.1 | 0.1 | 0.1 | 1.7 | 1.7 | 1.7 | 4.2 | 4.2 |
| Washington | 1 | 2.4 | 2.4 | 2.4 | 0.2 | 0.2 | 0.2 | 2.4 | 2.4 | 2.4 | >1,000 | >1,000 |
| Total | 104 | 4,584 | 812.0 | 0.1 | 178.8 | 33.8 | 0.0 | 4,584 | 812.0 | 0.1 | >1,000 | 0.3 |