Frameworks for Assessing the Vulnerability of U.S. Rail Systems to Flooding and Extreme Heat

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Mikhail Chester, Ph.D.
Assistant Professor
mchester@asu.edu

Andrew Fraser
Graduate Student
andrew.fraser@asu.edu

Matthew Bartos
Research Scientist
matthew.d.bartos@gmail.com

Civil, Environmental, and Sustainable Engineering
Arizona State University

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1 Introduction

Recent climatic trends show more flooding and extreme heat events and in the future transportation infrastructure may be susceptible to more frequent and intense environmental perturbations. Our transportation systems have largely been designed to withstand historical weather events, for example, floods that occur at an intensity that is experience once every 100 years, and there is evidence that these events are expected become more frequent. There are increasing efforts to better understand the impacts of climate change on transportation infrastructure (NRC, 2008). An abundance of new research is emerging to study various aspects of climate change on transportation systems. Much of this research is focused on roadway networks and reliable automobile travel. We explore how flooding and extreme heat might impact passenger rail systems in the Northeast and Southwest U.S..

1.1 Climate Change, Flooding, and Extreme Heat

In the Northeast U.S. average annual temperatures have increases by 2ºF and average winter temperatures by 4ºF. Heavy precipitation events have increased in both magnitude and frequency and the majority of precipitation now falls as rain, not snow (USGCRP, 2009, EPA, 2015). This combination of temperature rise and increasing precipitation has increased the risks from flooding. Furthermore, the rate of sea level rise in the Northeast exceeds the global average of approximately 8 inches (USGCRP, 2009).

Average temperatures in the Southwest U.S. have increased 1.6ºF (+/- 0.5ºF) from 1901-2010, with isolated areas experiencing increases up to 3.6ºF (SWA, 2012). Summer heat waves are also expected to become more frequent and intense around the globe (Meehl and Tebaldi, 2004), including in the Southwest (Miller et al., 2008). Throughout the United States, the frequency of extreme heat (or temperatures closely correlated with sharp increases in human mortality) has increased by about 20% over the last fifty years (Gaffen and Ross, 1998).

1.2 Climate Change and Passenger Rail

There are a variety of ways in which climate change can impact passenger rail systems. In this report we focus on how flooding might impact tracks in the Northeast and how extreme heat events are likely to create greater demand for electricity thereby pushing electrical distribution systems closer to their capacities, compromising reliable electricity delivery to rail systems. We start by describing how the life cycle assessment (LCA) framework can be used to assess climate change vulnerability in passenger transportation systems. Then, using case studies in the Northeast and Southwest, we present methodologies for assessing how flooding and extreme heat can impact long-distance and local passenger rail systems. The findings are relevant to current long-distance (i.e., Amtrak), future long-distance (high-speed rail) and urban rail systems.

2 Life Cycle Vulnerability Assessment

The LCA framework has primarily been used to assess the environmental impacts of products, processes, services, activities, and the complex systems in which they reside, and can be positioned to inform vulnerability mitigation strategies for passenger transportation systems. We use LCA as a guiding framework to assess rail life cycle processes that may be affected by flooding and extreme heat, and develop case studies for the Northeast and Southwest U.S. to explore vulnerabilities. While we focus on only a few life cycle processes (primarily infrastructure design and operation, and energy production and deliver) in the provision of passenger rail services, the vulnerability LCA framework (further referred to as vLCA) could be used to assess how vehicle (manufacturing and maintenance), infrastructure (construction, operation, maintenance, and rehabilitation), and energy production processes are affected by climate change, in addition to vehicle propulsion. We view vLCA as a form of anticipatory LCA in that it can aid policy and decision makers in understanding how components of transportation infrastructure are vulnerable to climate change and how to proactively govern and invest resources towards reducing vulnerabilities. Life cycle processes of rail systems are shown in Table 1 and are based on the assessments of Chester and Horvath (2009) and Chester et al. (2012).

Table 1: Passenger Rail Life Cycle Processes

	Passenger Rail Life Cycle Processes
VEHICLE	
Manufacturing	▪ Train Manufacturing ▪ Transport to Point of Use
Operation/Propulsion	▪ Propulsion (Electricity Generation) ▪ Idling (Electricity Generation)
Maintenance	▪ Train Maintenance
INFRASTRUCTURE	
Construction	▪ Tracks ▪ Terminals
Operation	▪ Track Lighting ▪ Herbicide Use ▪ Train Control ▪ Equipment
Maintenance/Rehabilitation	▪ Track Maintenance
ENERGY PRODUCTION & DELIVERY	
Extraction & Processing	▪ Primary Fuels Extraction and Processing ▪ Transmission & Distribution

We assess how flooding (urban and coastal) and extreme heat can impact (long-distance and local) passenger rail systems by focusing on a subset of the life cycle processes shown in Table 1. A methodology for assessing how flooding can impact Northeast U.S. rail systems is developed focusing on infrastructural processes. A methodology for assessing how the design of electricity distribution infrastructure and the ability of the electricity network to provide demand for rail electricity is developed for Southeast U.S. cities (Phoenix, Arizona and Los Angeles, California). These studies begin to develop insight into how electric passenger rail systems in the U.S. will be impacted by climate change and how LCA can be positioned to aid policy and decision makers in proactively mitigating these vulnerabilities.

3 Methodology for Assessing the Vulnerability of Rail Systems to Flooding

As a region, the Northeast is one of the densest in the country which makes it well-suited for passenger rail service. The proximity of major U.S cities including Washington D.C., Baltimore, Philadelphia and Boston have facilitated the development of an already well-utilized passenger rail system and population growth projects have increased interest for future investments to expand and improve existing services (e.g. upgrading Amtrak's Acela line to high-speed). At the same time, the Northeast is expected to experience impacts from climate changes that may threaten existing infrastructure and should be accounted for when developing plans for new infrastructure and services. Notably, climate projections forecast rising sea levels and more frequent and severe precipitation resulting in coastal storm surges and inland flooding. These extreme weather events could threaten day-to-day passenger rail operations as well as the long-term stability of the rail infrastructure and the health of the people they provide service to.

3.1 Consequences to Infrastructure and Service

More frequent and intense precipitation can negatively impact rail infrastructure in several different ways and while some may result in immediate consequences others may contribute to a slow deterioration of components. Table 1 details the potential climate effects of more precipitation and their infrastructure consequences. We propose a methodology to assess the vulnerability of existing passenger rail infrastructure to flooding resulting from the increasing frequency and severity of extreme storms. The methods are generalizable to other climate effects and infrastructure systems.

Table 2: Climate Impacts on Rail Infrastructure (Oslakovic et al., 2013)

	Impact	Consequences
Heavy Precipitation	▪ Flooding	▪ Rail embankment and slope damage ▪ Scour of bridge supports ▪ Flooding of underground structures ▪ Damage to rail track ▪ Material damage to other equipment and infrastructure components
Snowfall	▪ Flooding ▪ Freezing ▪ Damage to cables ▪ Loss of electricity ▪ Track obstructions	▪ Same as heavy precipitation
High Winds	▪ Coastal storm surge (flooding) ▪ Same as snowfall	▪ Supply cable sag, tensional failure ▪ Same as heavy precipitation
Low Temperatures	▪ Damage to cables ▪ Loss of electricity ▪ Freezing and frost	▪ Material damage to equipment and infrastructure ▪ Frost cracking, freezing of equipment and structures on track ▪ Supply cable sag, tensional failure ▪ Damage to rail track

3.2 Vulnerability Assessment Methodology

A three-step method is utilized to assess the vulnerabilities of Northeast passenger rail systems based on a methodology proposed by Oslakovic et al. (2013). First, a review of existing literature on infrastructure failures resulting from weather effects, including scholarly, industry-focused and design principles will be conducted to understand the causal link between extreme weather events and infrastructure impacts. A synthesis of this literature forms the basis of a model which would predict the probability of infrastructure impacts and consequences to extreme weather scenarios. These probabilities are based upon threshold values for flooding determined from the literature. Secondly, the current Northeast passenger rail system is studied in conjunction with climate predictions to identify the geographic locations where infrastructure is more likely to be impacted by future weather events. In this step we also identify critical sections of the infrastructure such as bridges and heavily utilized rail links. The final step synthesizes the first two to create a probabilistic assessment of risk to individual components and then prioritizes individual components for preventative maintenance and rehabilitation.

3.3 Inland and Coastal Flood Potential

The increasing severity and frequency of storms in the Northeast will lead to increasing runoff and flooding which has the potential of inundating low-lying rail lines. Additionally, increased storm surge will likely impact facilities at or below sea level along the Eastern seaboard. Similarly, sea-level rise may inundate and damage low-lying coastal rail infrastructure components. In addition to immediate consequences, reoccurring rain runoff and flooding can slowly undermine critical structural elements including bridges and railway beds and also contribute to the deterioration of secondary infrastructure (dams, electricity distribution) which may also impact passenger rail service. The likelihood of floods impacting passenger rail systems is based upon the location of Federal Emergency Management Agency's 100 Year Flood Zones and the location of passenger rail infrastructure (FEMA, 2015). The 100 year flood plan predicts where there is a 1% chance of flooding every year. However, climate models predict the increasing frequency and severity of extreme storms so the probability of what is currently described as a 100 year event is likely to increase. Alternative flooding scenarios are developed from climate forecasts. In addition to area flooding we propose that the magnitude of stream flow (which is correlated with the magnitude of flooding impacts) is also considered. Normal and flood stream flows available from the USGS should be utilized (USGS, 2015). The assessment should include rail infrastructure associated with both commuter rail systems and Amtrak along the 450 mile Northeastern Corridor stretching from Washington D.C. to Boston, Massachusetts (Figure 1) (FRA, 2014, FRA, 2015). This includes 17 tunnels and approximately 1,200 rail bridges.

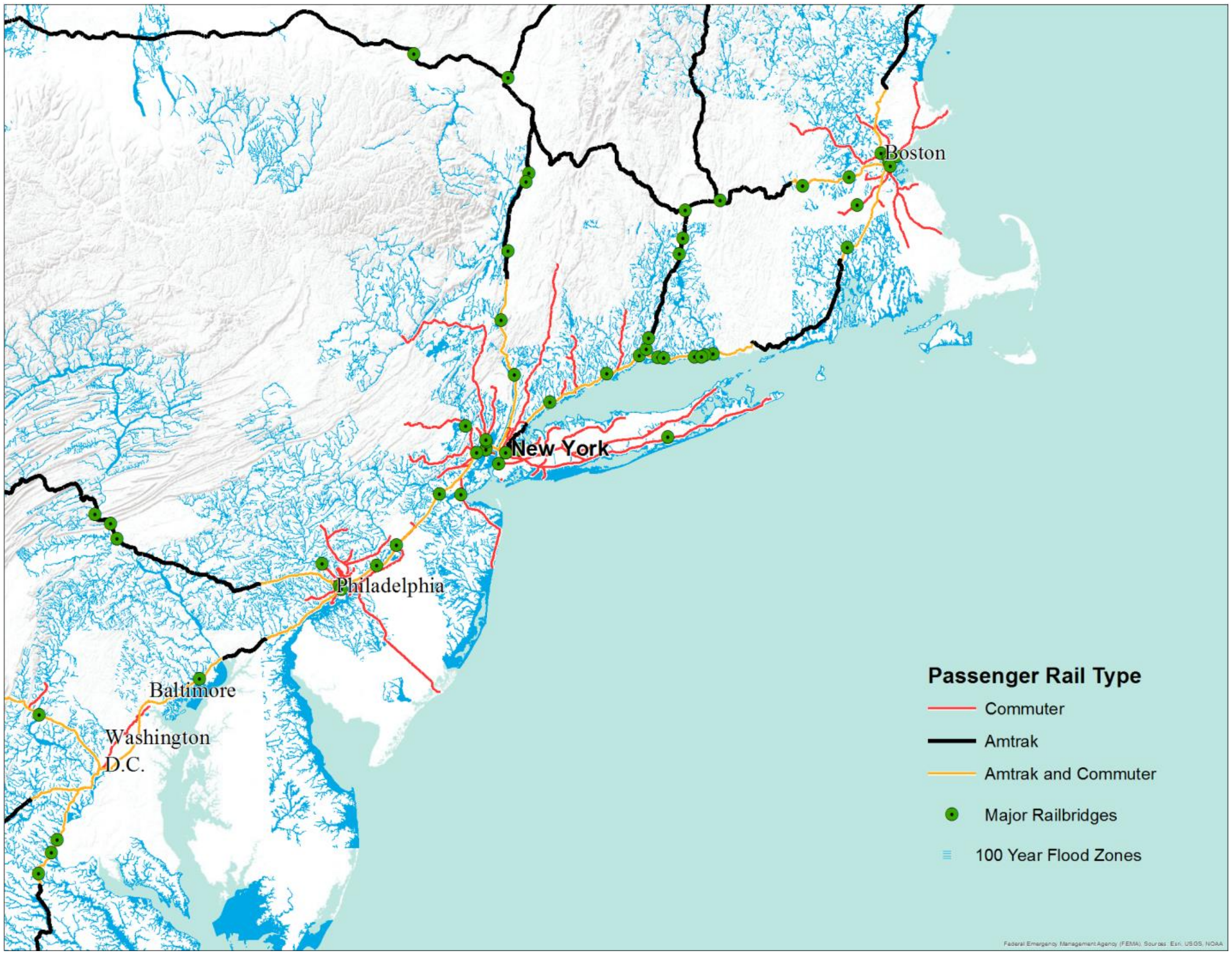

Figure 1: Northeastern Corridor Passenger Rail – Infrastructure Components and FEMA 100 Year Flood Planes

3.4 Conclusion

The methodology presented here provides a basic framework for assessing the risk and vulnerability of northeastern passenger rail to flooding impacts resulting from climate change. These estimates should be largely based on a model utilizing historical infrastructure failures and hypothetical impacts based on historical engineering design standards. Due to the uncertainty associated with the increasing frequency and severity of extreme weather events these methods likely lead to a conservative estimate of risk. As rail infrastructure ages and extreme weather events increase, resulting failures should be continually added to future iterations of the risk assessment model.

4 Methodology for Assessing Reliable Electricity Supply to Rail with Extreme Heat

4.1 Introduction

Electric rail reliability may be jeopardized by power shortages resulting from future extreme heat events. Extreme heat events pose a threat to electric power reliability because they result in increased electricity demand while simultaneously causing decreased generation and transmission capacity. Electricity demand is typically largest during periods of high ambient temperature, due to air conditioning loads. At the same time, extreme heat and drought may limit the available generation capacity at thermoelectric, hydroelectric and photovoltaic power facilities. Transmission lines and substations are also most likely to run up against thermal limits during periods of high ambient temperature. During extreme heat events, these effects interact in unpredictable ways, and may result in electricity shortages. Over the next fifty years, extreme heat events are expected to occur with greater frequency, intensity and duration; however, the combined effects of climate change on electricity generation, transmission and demand are currently not well understood. In this study, we assess potential power distribution bottlenecks arising from extreme heat events, and how they may affect future electric rail reliability. To evaluate potential points of failure in the system, we use a bottom-up approach:

1) Temperature-load response functions are created for relevant utilities to determine the increase in electricity load for a given increase in temperature.
2) Loads at each substation are estimated by using a Voronoi tessellation to partition the utility service area into areas served by individual substations.
3) Thermal limits of power lines are determined based on meteorological forcings and characteristic power line properties.
4) A network model is forced with expected loads and meteorological forcings to determine where failures are most likely to occur.

The results of this analysis are used to determine where electric power shortages are most likely to occur in the transmission network, and to estimate the probability that electric rail reliability may be affected by future extreme heat events.

4.2 Determining the temperature-load response function for utility service areas

Extreme heat events may strain power transmission infrastructure by incurring large coincident peak loads. Electricity shortages were reported in 1998 during record temperatures in the Western United States (CEC, 1999). Stage II alerts were issued on several occasions during this period by the California Independent System Operator, signaling that operating reserves had fallen below 5 percent (CEC, 1999). During this time, interruptible-load customers were asked to curtail electricity usage such that a 5 percent reserve margin could be maintained (CEC, 1999). Following this event, the California Energy Commission developed a study in 1999 to examine the relationship between temperature and electricity demand for 67 utilities in the Western Systems Coordinating Council region. The study found that "small changes in average temperature … had a large impact on peak demand" (CEC, 1999). As the Southwestern U.S. becomes hotter and drier, electricity shortages may become more commonplace. To determine potential increases in electricity load due to climate change, we develop temperature-load response functions for each utility service area in the Southwest based on historical temperature and electricity demand data. For each utility service area, the four following steps are applied to determine the temperature-load response function: (i) hourly electricity load data are collected for the period 1993-2013, (ii) census tract data are used to construct population estimates for the period 1990-2010, (iii) the effect of long-term population growth is removed from hourly electricity load, and (iv) detrended hourly electricity load data are combined with hourly temperature data in a regression model to determine the expected increase in electricity load for a given increase in temperature.

To isolate the effect of temperature on electricity demand, the effect of population growth must first be removed. Time series of electricity demand data can typically be separated into a long memory component and a short memory component. The long memory component reflects year-to-year changes in population, electricity prices, and demographic characteristics. The short memory component reflects periodic trends in electricity demand and is mainly attributable to changes in temperature. To isolate the short memory component of electricity demand, hourly loads from 1993-2013 are first determined for major electrical utilities in the WECC region using data from FERC Form 714 (FERC, 2015). Next, the population of each utility service area is estimated over the same time period. This process takes place in three steps: (i) population estimates are collected at the census tract-level for the years 1990, 2000 and 2010 (Census, 1990a, Census, 2000a, Census, 2010), (ii), the census tracts contained within each utility service area are determined using a spatial join (Census, 2014a, Census, 2000b, Census, 1990b, DHS, 2014a), and (iii) populations of all "contained" census tracts are summed to determine the total population within a utility service area. Having determined the population of each utility service area from 1993-2010, the long-memory component of electricity demand is isolated by constructing a regression between mean annual electricity load and mean annual population. This long-memory component is then subtracted from observed hourly load data to determine the short-memory component of electricity demand. Removing the effect of population growth yields the "detrended" load (normalized around zero), which represents the portion of load that can be attributed to fluctuations in temperature. This "detrended" load (referred to as the "load anomaly") is indicated by the green curve in Figure 2 (right panel).

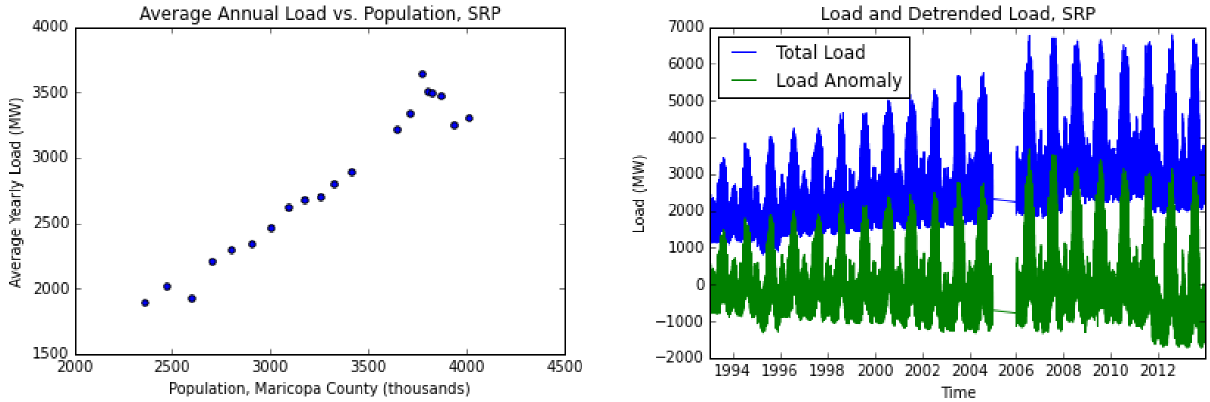

Figure 2. **(Left): average annual load for the Salt River Project (SRP) utility service territory vs. population growth in Maricopa County (which contains the utility service territory). (Right): Hourly demand for the SRP service territory (1993-2013) is shown in blue. Removing the effect of population growth from hourly demand yields the "detrended" load, which is indicated by the green curve. The green curve shows the "short-memory" component of hourly electricity demand (i.e. the portion of electricity demand that can be attributed to temperature effects) (Bartos and Chester, 2015).**

After removing the effect of population growth, hourly electricity demand is combined with observed temperature data to determine the relationship between hourly temperature and hourly load. Because not all utility service areas contain representative temperature gauging stations, historical gridded temperature data at a spatial resolution of 1/8 degree are used (Maurer et al., 2002). In Figure 3 (left), the load anomaly (i.e. the detrended load) is plotted against the temperature anomaly (which represents the hourly temperature's deviation from the annual mean temperature as a decimal fraction). This plot shows a strong positive correlation between air temperature and electricity load. However, the relationship is not linear. Rather, the plot of load anomaly vs. temperature anomaly exhibits a hysteresis loop, which likely reflects the effect of thermal storage in air conditioned buildings: buildings heat up during the morning hours, following the lower bound of the loop. After reaching a peak (when daily temperature is greatest), the load begins to decrease over the evening and nighttime hours, following the upper bound of the loop. The highest hourly temperatures are associated with the highest hourly electricity loads. For each utility service area, a logistic regression is used to relate a given load anomaly to a given temperature anomaly. Linear regressions are also used to relate daily peak loads with daily maximum temperatures (see Figure 3, right).

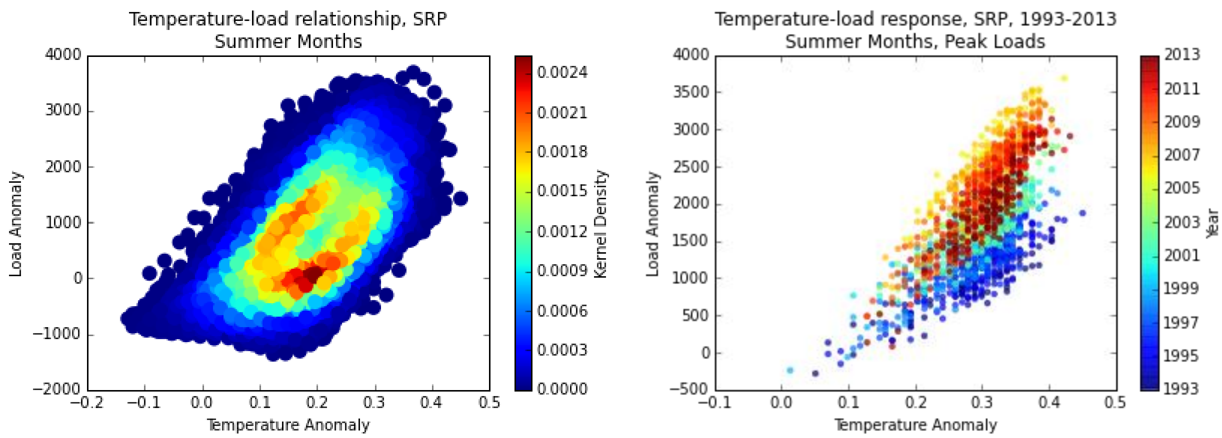

Figure 3. (Left) **Temperature-load relationship for the Salt River Project (SRP) service territory during summer months (June, July and August). The horizontal axis represents the temperature anomaly (the degree to which temperature exceeds the mean temperature as a decimal fraction). The vertical axis represents the load anomaly (hourly electricity load with the effect of population growth removed, normalized around zero). Colors represent the kernel density of observed values (with red and yellow areas corresponding to a greater number of observations). Note that the relationship between temperature and load exhibits a hysteresis loop, most likely resulting from the effects of building thermal storage: buildings heat up during the day, following the lower bound of the loop, then cool off at night, following the upper bound of the loop. (Bartos and Chester, 2015) (Right) The relationship between maximum daily temperature and peak load is nearly linear; however, the slope of the relationship varies from year to year, and is influenced by socioeconomic factors.**

Some utility service areas (such as the Arizona Public Service Co.) span multiple climate zones and population centers. For these utilities, a single representative temperature cannot be used to determine the relationship between temperature and electricity demand. Instead, multiple regression is used to relate temperatures at major population centers to total electricity load. First, major population centers in each utility service area are determined using the U.S. Census Bureau's Urban Areas dataset (Census, 2014b). Gridded observed temperatures at each urban area are then used in a multiple linear regression relating daily hourly temperature to electricity demand. The populations of the representative urban areas are used as the initial weightings in this multiple regression.

4.3 Estimating electricity load at electrical substations

Power failures typically do not occur everywhere at once within a transmission network, but rather occur at the "weakest link" in the system. To determine the probability of intra-urban electricity shortages, it is necessary to estimate electrical loads at individual transmission lines and substations such that the most vulnerable regions of the network can be identified. In this section, we outline a method for estimating component-scale loads based on hourly utility-scale demand and housing densities.

Electricity load at the sub-utility scale is generally not accessible to the public. To estimate loads at individual substations, utility-level demand data are downscaled to component substations by (a) determining the approximate region served by each substation, and (b) determining the number of housing units located in each of these regions. First, to determine the approximate area served by each substation, a Voronoi tessellation is generated, with substation locations representing the "seed" points of each Voronoi cell (DHS, 2014b). Voronoi tessellation is a method of partitioning a plane into unique regions based on a set of "seed points". For each seed point, Voronoi tessellation yields a corresponding region consisting of all points closer to that seed point than any other. In this case, the cells generated by the Voronoi tessellation represent the area that is closest to each substation to the exclusion of all other substations. After determining the approximate region served by each substation, the relative load at each substation is estimated based on the number of houses in each Voronoi polygon. To this end, we use gridded housing density data from the EPA's ICLUS dataset for the year 2010 (EPA, 2010). The EPA ICLUS dataset is used because it offers housing density data at a fine scale, contains projected populations up to the year 2100, and is integrated with SRES climate scenarios. Figure 4 and Figure 5 show Voronoi tessellations for Los Angeles and Maricopa counties, respectively. The color of each Voronoi cell indicates the approximate load at the contained substation.

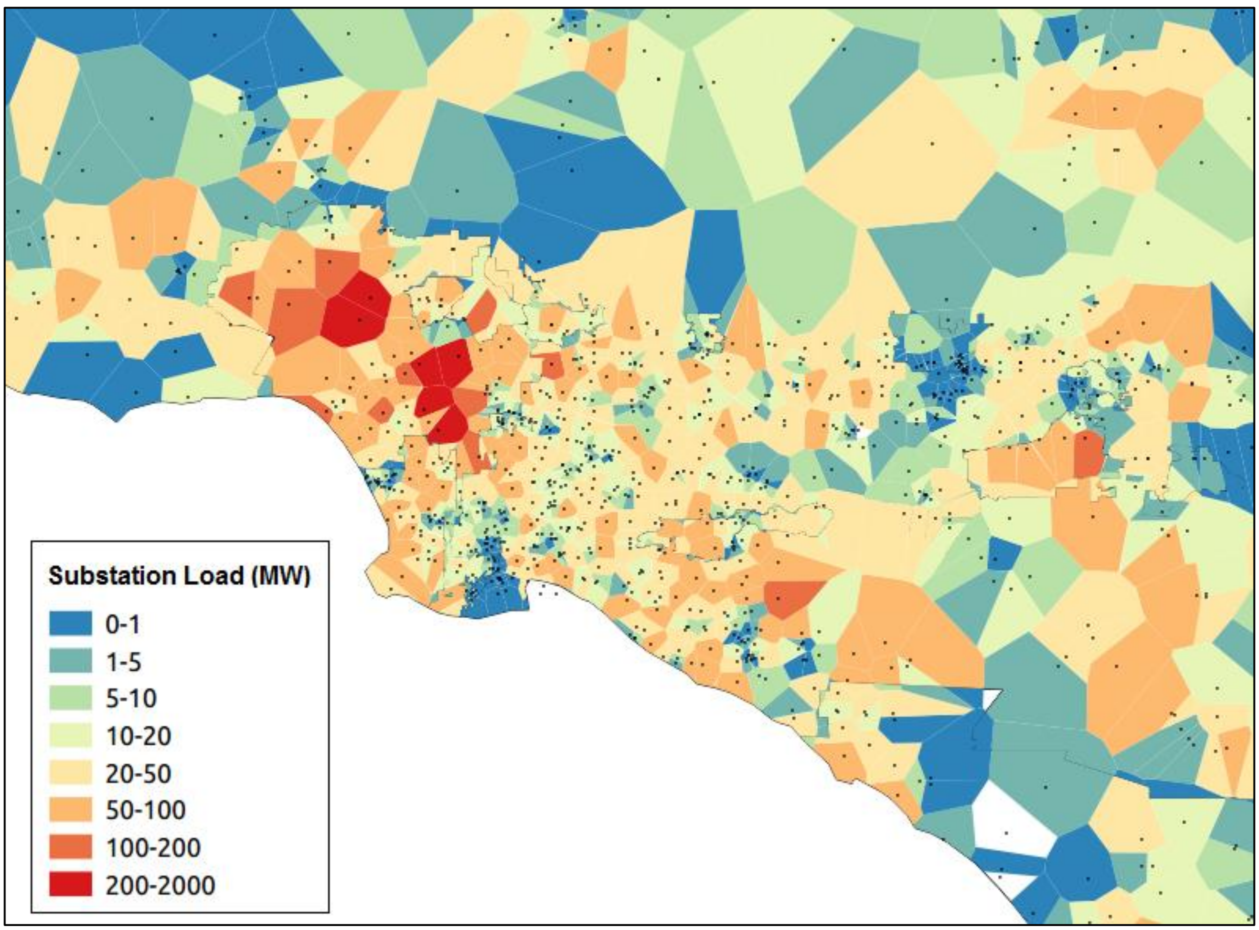

Figure 4. Voronoi tessellation of Los Angeles electrical substations. Substations are indicated by black dots, while the colored regions indicate the Voronoi cells. The color of the Voronoi cell indicates the load, in MW, with blue cells representing small loads, and red cells representing large loads.

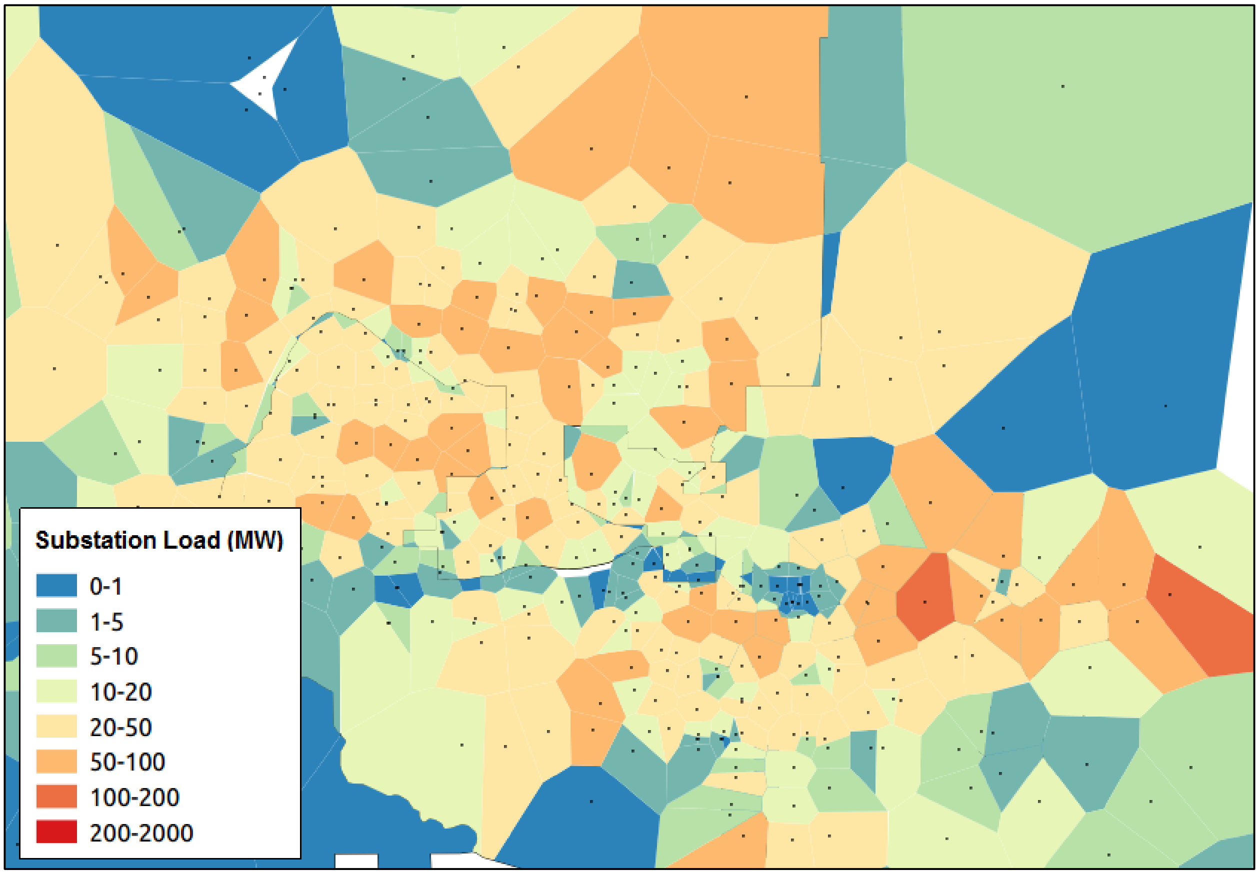

Figure 5. Voronoi tessellation of Maricopa County electrical substations. Substations are indicated by black dots, while the colored regions indicate the Voronoi cells. The color of the Voronoi cell indicates the load, in MW, with blue cells representing small loads, and red cells representing large loads.

4.4 Determining the thermal limits of electrical transmission lines

Extreme heat events may contribute to electricity shortages by causing transmission lines to surpass their thermal ratings. Thermal ratings represent the maximum capacity at which an overhead conductor can operate for given weather conditions. Continued operation beyond a conductor's thermal rating can result in excessive sag or damage to the conductor (IEEE, 2006). To avoid damage, utilities typically either curtail the current in an at-risk conductor, or shut off power to than conductor entirely. Additionally, transmission lines suffer incremental power losses at elevated conductor temperatures, meaning that elevated temperatures could result in reduced transmission capacity even when thermal limits are not breached (IEEE, 2006).

Thermal ratings (i.e. design ampacities) are determined based on a maximum allowable conductor temperature, meteorological conditions, and conductor characteristics (such as the geometry of the conductor and its material properties) (IEEE, 2006). The thermal limits of overhead conductors are estimated using a steady-state heat balance (IEEE, 2006):

$$q_c + q_r = q_s + I^2 R(T_c)$$

Where q_c represents the convected heat loss rate per unit length (W/m), q_r represents the radiated heat loss rate per unit length (W/m), $q_s$represents the heat gain rate from the sun (W/m), I represents the conductor current (A), $R(T_c)$ represents the AC resistance of the conductor at temperature T_c (Ω/m). This heat balance can be rearranged to yield the maximum current for a design conductor temperature:

$$I = \sqrt{\frac{q_c + q_r - q_s}{R(T_c)}}$$

Design ampacities are calculated for each transmission line in the area of interest based on characteristic transmission line designs and meteorological forcings (i.e. temperature and wind speed) at design conditions (IEEE, 2006). These design ampacities are then used as inputs to a load-balancing simulation, which aims to determine where power shortages are most likely to occur within a transmission network.

4.5 Estimating transmission bottlenecks

After determining the effect of climate change on both electricity demand and electricity transmission capacity, a load-balancing model is forced with projected meteorological data to determine the extent to which elevated temperatures may induce power shortages. In this model, power shortages occur when peak demand cannot be satisfied—either because the temperature-induced demand exceeds the carrying capacity of the connecting lines, or because exceedance of thermal ratings results in a momentary power outage. The load balancing model is forced with downscaled outputs from three GCM models and three carbon emissions scenarios for the period 2010-2050. For projections of temperature and wind speed, gridded forcings from the CMIP3 multi-model are used (DOI, 2013). The load-balancing model is used to deliver a first order estimate of which transmission lines are most at risk of power shortages. Impacts to rail lines are expected to occur if the substations serving these rail lines are susceptible to frequent power outages under future extreme heat events.

4.6 Conclusion

This study uses a bottom-up approach to determine how electric rail reliability may be affected by power shortages resulting from future extreme heat events. This process takes place in four steps. First, temperature-load response functions are developed for each utility in the Southwest, such that peak loads resulting from future extreme heat events may be predicted. Second, utility-level electricity demand is allocated to substations within each utility service area using a Voronoi tessellation approach. Next, thermal limits are determined for each transmission line in the location of interest based on transmission line characteristics along with wind speed and temperature forcings. Finally, using the substation-level loads and thermal ratings developed in the previous steps, a load-balancing simulation is used to determine the probability of power shortages under future extreme heat events, and to determine the location within the network at which failures are most likely to occur. The results of the load-balancing simulation are used to determine whether substations serving electric rail lines are likely to experience power shortages. In this way, the reliability of electric rail under future extreme heat events can be assessed.

5 Discussion

5.1 Positioning LCA for Climate Change Vulnerability Assessment

Currently there exists no systems-oriented framework for proactively managing the potential vulnerabilities associated with climate change to passenger transportation systems and the vLCA framework offers significant opportunity for guiding decision makers towards protecting their systems, including vehicle, infrastructure, and energy production components, in addition to propulsion. LCA has traditionally focused on quantifying environmental effects. However, the framework is well-suited for structured decomposition of complex passenger transportation systems to understand, from material and primary fuel extraction, transformation into finished products, use, maintenance, rehabilitation, and operation of the vehicles, where vulnerabilities will exist due to environmental perturbations, and how those vulnerabilities may cascade through the system. While we do not offer a case study in this report that comprehensively uses vLCA, we instead intend to setup the framework for future studies of passenger transportation systems.

5.2 Ensuring Rail Service with Climate Change

The flooding and extreme heat case studies impact infrastructure use and vehicle operations, which have the potential to create major service disruptions, and service providers can protect existing and future systems with proactive management strategies. Engineers should recognize that flooding events that occurred with low frequencies (e.g., once in 100 years) are forecast to occur with greater frequency (USGCRP, 2009). As such, design standards which likely follow historical weather events, should be updated to account for these greater frequencies. We should also recognize that more frequent and more intense precipitation events are likely to increase our transportation system's exposure to water. Proactive management strategies for flooding should consider:

- Electrical components should be protected with more robust insulation or raised above or moved away from potential water intrusion.
- The design of track beds should be reassessed to ensure that they maintain their structural integrity.
- Station designs should be reconsidered to protect passengers (in both safety and comfort) from the increases in precipitation.
- Protections should be afforded for ingress to and egress from stations.

Similarly, physical components of transportation systems and passengers are likely to experience more frequent and intense exposure to extreme heat, particularly in the U.S. Southwest (Bartos and Chester, 2014). Extreme heat is likely to impact passenger transportation systems through a number of pathways. As such, proactive management strategies should consider:

- Reassessing the design specifications of physical components of vehicles and infrastructure to ensure that they will reliably perform during hotter temperatures over longer durations.
- Protecting people through increased use of shading, fans, and misters (structural and natural) at stations and during ingress and egress.
- Implementing renewable energy generation systems for electricity delivery for propulsion, station operations, and track and signal control.
- Reassessing transmission and distribution network capacity to ensure that rail systems will receive reliable and sufficient supply during times of increased demand.

It's important to recognize that large-scale system failures can stem from component failures that cascade through the system (Chester, 2013). Strategies to protect transportation systems against climate change must take an entire systems view.

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