

ANALYSIS OF INDIRECT EMISSIONS BENEFITS OF WIND, LANDFILL GAS, AND MUNICIPAL SOLID WASTE GENERATION

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Notice

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Abstract

A number of techniques are introduced to calculate the hourly indirect emissions benefits of three types of renewable resources: wind energy, municipal solid waste (MSW) combustion, and landfill gas (LFG) combustion. These techniques are applied to each of the U.S. EPA's eGRID subregions in the continental United States in order to derive hourly, seasonal, or annual (as appropriate) coefficients for use in evaluating the indirect emissions benefits of such projects in each region.

For wind power impacts, simulated wind project power profiles are derived using publicly available wind data scaled to a typical turbine height for new wind projects and transformed through a power curve for a proxy turbine. The results for one region are compared to the output of an existing project, although the limitations of this type of comparison, as well as the limitations of representing large areas of the country with single proxy curves, are discussed. Landfill gas and MSW are found to have flat, "always on" profiles based on the limited data available.

The regional, hourly power profiles for each type of resource are combined with the hourly indirect emissions coefficients to yield annual indirect emissions benefits for each type of resource for each eGRID subregion.

For each GWh of renewable energy produced each year, the indirect CO₂ emissions benefit is found to be between 600 and 1100 tons of CO₂ depending on the region, with coal-dependent regions having the highest indirect emissions benefit. The indirect NO_x and SO₂ emissions benefit also depends on the regional fuel mix, as well as the stringency of environmental regulation in each region. These indirect emissions benefits vary between 500 and 5,000 pounds of NO_x per GWh, and between 200 and 1,300 pounds of SO₂ per GWh. With some exceptions, these results are robust regardless of whether the renewable resource has a base load profile (such as MSW and LFG) of output which varies diurnally and seasonally (such as wind). However, as the calculated benefits do vary in some cases depending on the analytical approach, care must be used in selecting an appropriate calculation methodology for each application.

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Acronyms and Abbreviations

AWEA	American Wind Energy Association
BTU	British Thermal Unit
CO ₂	Carbon Dioxide
DOE	U.S. Department of Energy
eGRID	Emissions & Generation Resource Integrated Database
EIER	empirical incremental emission rate (defined in this study)
EPA	United States Environmental Protection Agency
FW-HAER	flexibility-weighted hourly average emission rate (defined in this study)
GE	General Electric
GW	gigawatt
GWh	gigawatt-hour
HAER	hourly average emission rate (defined in this study)
kW	kilowatt
kWh	kilowatt-hour
LFG	landfill gas (generating resource)
LFIR	load-following incremental emissions rate (defined in this study)
mmBTU	million British thermal units
MSW	municipal solid waste (generating resource)
MW	megawatt
MWh	megawatt-hours
NCDC	National Climatic Data Center
NERC	North American Electric Reliability Corporation
NOAA	National Oceanic and Atmospheric Administration
NO _x	mono-nitrogen oxides (NO and NO ₂)
NREL	National Renewable Energy Laboratory
SO ₂	sulfur dioxide
WBAN	Weather Bureau Army Navy

List of Appendices

Appendix A

Identification and map of eGRID subregions

Appendix B

Synthetic wind power time series (hourly percent of capacity) for each eGRID subregion, represented as color intensity plots

Appendix C

Summary tables of raw and scaled wind speed and synthetic wind power time series

Appendix D

Color intensity maps of hourly indirect CO₂, NO_x and SO₂ emissions rates for each eGRID subregion, using several alternative calculation methodologies

1. Introduction and Summary of Conclusions

The purpose of this report is to develop, analyze, and report upon methods of quantifying the indirect emissions benefit associated with renewable energy generation resources. In particular, the goal is to conduct a national assessment of indirect emissions reductions from wind, landfill gas (LFG), and municipal solid waste (MSW) by NERC subregion.¹ Because conventional electricity generation resources can differ widely in their emissions characteristics, the determination of exactly which conventional resource or resources would be running but for the contribution of the renewable resource would be the ideal first step in calculating indirect emissions benefits. If we knew which resources were “displaced” by the renewable resource, we could simply multiply the emission rate of those resources by the total number of megawatt-hours (MWh) displaced, accounting for line losses, and an exact answer would be obtained. The answer thus obtained would vary from region to region, and from hour-to-hour within any given region, depending on current and expected market conditions.

Unfortunately, in large, interconnected, security-constrained² electricity markets, determining which units would be displaced in any given hour would require perfect information and a complex dispatch model. Even under such ideal circumstances, the analysis would be prohibitively time-consuming and complex for each hour. Thus our goal in the current study is to develop and apply proxy methods that, while imperfect, are applicable to and useful for the general estimation of the indirect emissions benefits for renewable energy projects anywhere in the continental United States. Over the course of this report, we develop and apply these methods to estimate the indirect emissions benefits of three kinds of renewable energy projects, for carbon dioxide (CO₂), sulfur dioxide (SO₂) and oxides of nitrogen (NO_x), in each of the 22 eGRID³ subregions of the continental United States.

An “indirect emissions benefit” may be a real reduction in total emissions in a region or, under cap-and-trade regulation such as that in much of the United States for the pollutants SO₂ and NO_x, it may be an opportunity to release emissions allowances for some other use. The calculation methods explored in this report are appropriate for either application, but the impacts of these scenarios are quite different in terms of their ultimate effect on pollutant emissions. In the case of cap-and-trade regulation, displacing air emissions provides an opportunity for the allowance holder to sell or bank valuable emissions allowances. There may also be a societal benefit in terms of reducing the market price of emissions allowances, thereby reducing this component of the cost of

¹ EPA RFQ # RFQ-OH-07-00015, as posted at: https://www.fbo.gov/?s=opportunity&mode=form&id=556118954b3728ae31326b103396bcf6&tab=core&_cview=0.

² “Security constrained” refers to the need for system operators to dispatch generating units to meet load while respecting the loading on transmission lines and interfaces within their operating limits. Because of these security constraints, generating units cannot simply be dispatched in merit order, from least expensive to most expensive running costs. In many cases more expensive units must be run out of merit order due to transmission transfer limits.

³ The Emissions & Generation Resource Integrated Database (eGRID) is a comprehensive inventory of environmental attributes of electric power systems. (<http://www.epa.gov/cleanenergy/energy-resources/egrid/index.html>.) Definitions and a map of the eGRID subregions are shown in Appendix A. eGRID subregions are roughly coincident with NERC (North American Electric Reliability Corporation) subregions.

electricity. Finally, there may ultimately be a total emissions reduction if the lower cost and greater availability of allowances permits regulators to tighten the total emissions cap.

This report is organized as follows:

- In **Section 2**, we develop and present operating characteristics of wind, landfill gas, and municipal solid waste energy resources in each of the eGRID subregions of the United States. We develop hourly operating profiles for a “typical” such resource in each region, normalized to produce one GWh⁴ of electricity per year.
- In **Section 3**, we collect and present data on conventional power plants in each eGRID region based on the EPA’s Acid Rain database.⁵ We characterize the data and discuss our approach to data filtering and error handling, in preparation for characterizing the indirect emissions benefits associated with changes in dispatch.
- In **Section 4**, we implement and evaluate a number of approaches to applying the filtered and cleaned EPA data for the purposes of calculating hourly avoidable emissions factors. These factors can then be applied to renewable resource production profiles to calculate annual indirect emissions benefits. In addition, we present hourly indirect emissions results for each pollutant, region, and calculation approach under consideration, and we discuss which approaches make sense for which kinds of analyses.
- In **Section 5** we apply the indirect emissions calculation methods to determine indirect emissions benefits associated with each resource type under consideration for each region and pollutant.
- Finally, in **Section 6**, we discuss our results and present suggestions for further research in this area.

Fundamental to the analysis in this report, all of which is based on retrospective data, is the primary focus on short-term, operational response of the electric system to the presence of new renewable energy resources. This analysis is thus most appropriate for analyzing the impact of a relatively small quantity of new resources during the first few years of operation, during which the displaced resources are likely to be the most flexible, load-following units on the system. Over the long term, it is likely that the capacity mix of an electric system will be altered as a result of the addition of new renewable energy resources. Specifically, new generating capacity investments may be avoided or deferred, or existing capacity may be retired, until the system returns to equilibrium in terms of the balance of base load and load-following resources. Ultimately, it may be expected that the proportion of flexible units will be restored to what it would have been without the new resource. In this sense, as it matures and is incorporated in larger quantities, renewable energy technology will ultimately displace more base load capacity

⁴ A GWh (gigawatt-hour) is one thousand megawatt-hours, approximately the amount of power that could be produced by one of the largest power plants in the United States in one hour. For perspective, the largest new single wind turbines are about 3 MW in capacity but produce, on average, about one MWh of electricity per hour. Thus one of the largest wind turbines would be expected to produce about nine GWh of electricity each year. In general, wind *projects* have more than one wind *turbine*, and can have up to 200 or more.

⁵ Available from the EPA Clean Air Markets data website, at <http://camddataandmaps.epa.gov/gdm/>

on the system. While we touch on this important issue in some parts of this report, it is not a primary focus.⁶

The indirect emissions benefit calculated for any kind of renewable energy resource depends on a number of questions:

- Where is the resource located?
- What is the pollutant of interest?
- Is the time period of interest historical, in the near future, or several years in the future?
- Is the resource base load, dispatchable, or intermittent and nondispatchable?
- If intermittent and nondispatchable, what is the expected hourly and seasonal profile of the resource?

Because of the wide range of applications reflected in the possible answers to these questions, the best method to use in calculating indirect emissions benefits can vary with the application. In this report we present a number of methods, and apply them to three types of renewable resources and three pollutants in 22 regions of the United States. Even this level of detail is almost certainly insufficient for precise analysis of the emissions benefits of individual projects. However, it leads to illuminating and useful results that will allow for a far more detailed understanding of the issues and a better first approximation of the indirect emissions benefits than has previously been available.

We find:

- The indirect emissions benefits of renewable energy for all pollutants vary significantly by region, and that these differences can be quantified and applied in calculating the indirect emissions reductions.
- For each GWh of renewable energy produced each year, the indirect CO₂ emissions benefit is found to be between 600 and 1000 tons of CO₂, with coal-dependent regions having the highest indirect emissions benefit.
- For each GWh of renewable energy produced each year, the indirect NO_x emissions benefit varies between 500 and 5,000 pounds of NO_x.
- For each GWh of renewable energy produced each year, the indirect SO₂ emissions benefit varies between 200 and 1,300 pounds of SO₂.
- These results are robust regardless of whether the renewable resource has a base load profile (such as MSW and LFG) of output which varies diurnally and seasonally (such as wind).
- Different calculation approaches are appropriate for different types of resources and different applications.

⁶ For a thorough treatment of this issue, see 2005 Synapse report *Using Electric System Operating Margins and Build Margins: Quantification of Carbon Emission Reductions Attributable to Grid Connected CDM Projects*, available at <http://www.synapse-energy.com/>

- More research is needed to establish which methods of calculating indirect emissions changes most accurately reflect real-world dispatch over a range of timescales and system conditions.

Of the methods introduced here, we find the flexibility-weighted hourly average emission rate (FW-HAER) to be the most appropriate for near-term (<3 year) projections of indirect emissions impact from wind resources, because it best represents the response of the electric system to rapid fluctuations in system load. We find the seasonal slope factor approach to be most appropriate for calculating the indirect emissions impact from base load resources such as municipal solid waste and landfill gas electricity generation.

The annual indirect emissions results for these resources based on 2005 data, assuming one GWh of energy was produced by each over the course of the year, are shown in Figure 1. With some notable exceptions, the indirect CO₂ and NO_x emissions benefits of the different renewable energy resources is generally similar; this benefit diverges most dramatically by resource type for SO₂. This divergence probably reflects the fact that in many regions, base load resources like MSW and LFG can displace coal, which emits SO₂, while wind initially primarily replaces gas, which does not emit SO₂. However, with increasing penetration and geographic diversity of wind generation it is likely that this resource will begin to displace more base load coal, and the indirect emissions impact of wind generation will be closer to that of MSW and LFG.

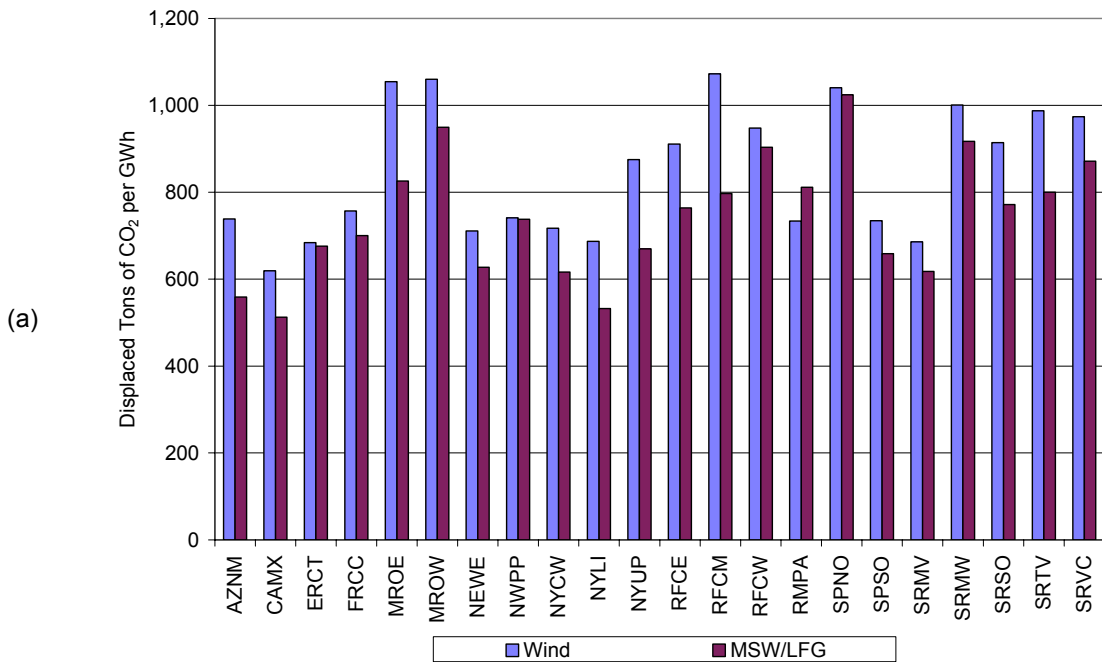


Figure 1. Indirect emissions results for (a) CO₂; (b) NO_x; and (c) SO₂ for wind, municipal solid waste (MSW) and landfill gas (LFG) generation projects. (Continued on next page)

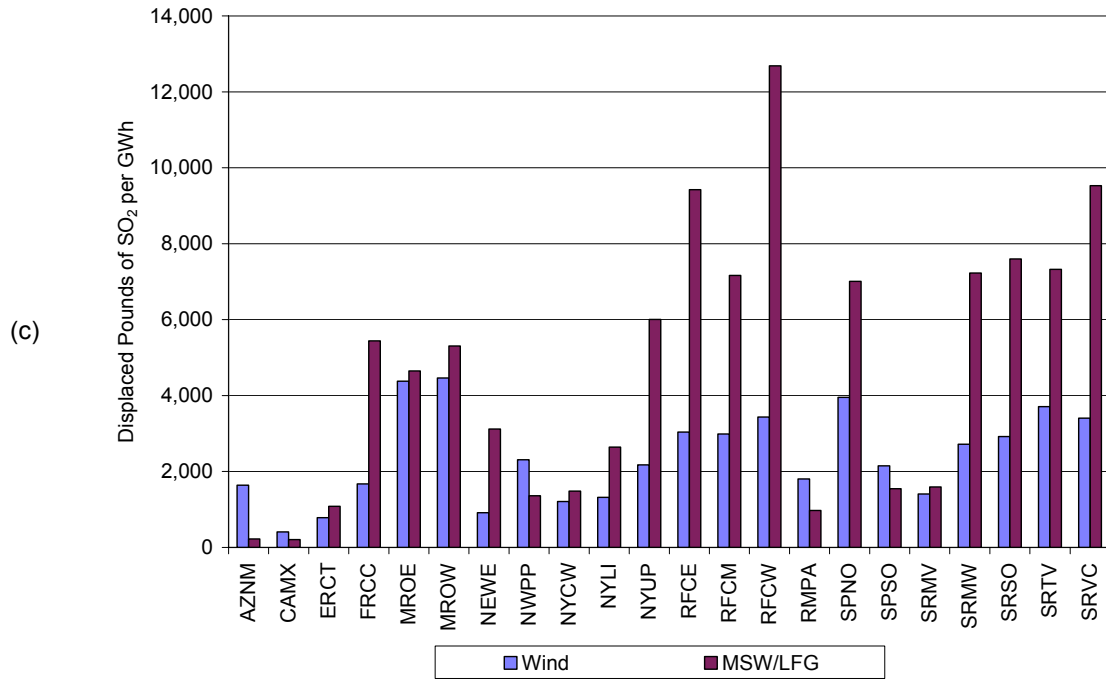
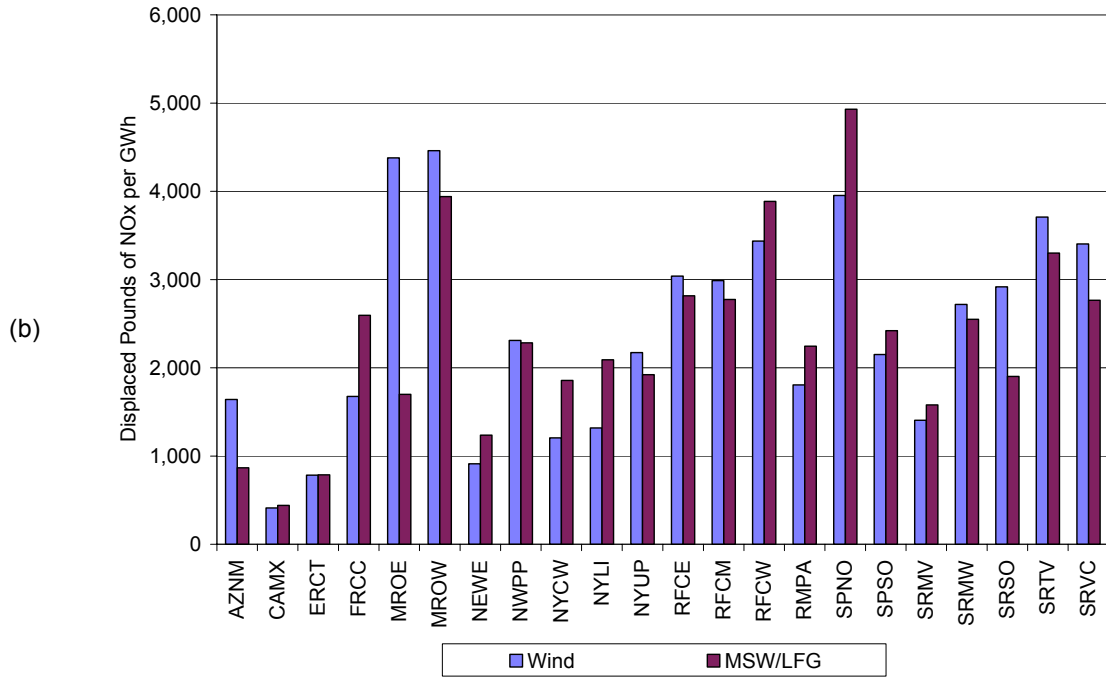


Figure 1 (Continued)

2. Operating Data on Renewable Energy Technologies

In order to determine the indirect emissions reduction impacts of electricity production from renewable energy sources, it is necessary to first establish what kinds of conventional resources they are displacing. As a first step, in this section of the report we explore the operational characteristics of three types of renewable energy resources: wind power generation, municipal solid waste combustion, and landfill gas. We develop profiles for these resources representative of each eGRID subregion of the continental United States⁷ based on historic data and operating characteristics of these resources. (The eGRID subregions are identified and mapped in Appendix A.) Once we have determined their hourly output profiles over the course of a historic year, we can begin an assessment of which resources they would have been likely to displace.

In the section that follows, we will explore corresponding operational and dispatch characteristics of conventional resources. Following that we combine the results of these research tasks, characterizing renewable energy output and assessing displaceable conventional resources, to make a final assessment of which fossil resources would have been likely to be displaced by renewables in each eGRID subregion. Finally, we use the results of this combined analysis to determine factors representing the indirect emissions benefit for each subregion.

A. Wind Generation: Existing and Synthetic Projects

The American Wind Energy Association (AWEA) estimates that there are approximately 8.3 gigawatts (GW) of installed wind capacity in the United States as of the 4th quarter of 2007, with another 4.1 GW under construction.⁸ Texas and California dominate the current market, but there are underutilized regions throughout the Midwest. Some states with the greatest wind potential, such as the corridor stretching from North Dakota south through Kansas, have yet to significantly tap this resource. In general, there are extensive opportunities to expand the rapid growth in wind generation, resulting in the further displacement of fossil fuel generation and decreased emissions of greenhouse gases and other pollutants. This large resource potential motivates the need to understand in more detail the emissions benefits associated with renewable energy projects in each region.

Ideally, to characterize the output profiles for new wind generation projects, we would draw empirical wind power output datasets from a broad sampling of existing projects around the country. Unfortunately, wind generation projects are not required to publicly report hourly generation, and thus there are limited opportunities to calculate expected emissions reductions from existing resources. In addition, “real” wind projects present numerous hurdles that make them problematic as a source of research data for a broad-based study of operational characteristics. For example, there is generally no uniformity, and often no available information, on the technical details of existing resources. With

⁷ eGRID subregions are almost coincident with NERC subregions. We chose to use eGRID subregions for this analysis as this is the system used by EPA for emissions reporting.

⁸ American Wind Energy Association, 2007. Updated information can be found at <http://www.awea.org/projects/>.

operational data available on few projects, what may appear to be regional differences in operating characteristics would be heavily influenced by unknown differences in technology, turbine size, turbine height, vintage, and specific local conditions associated with each individual project. In addition, the geographical coverage of available wind power output data is extremely limited. In fact, we were only able to find one source for such data, from the U.S. Department of Energy's National Renewable Energy Laboratory (NREL). This dataset covered only a small number of projects with limited geographic distribution. Even with this source we were asked not to present specific, identifiable details or operational data to avoid disclosure of proprietary information, limiting its usefulness for our study.

Our solution to these limitations is to simulate wind power projects based on meteorological data gathered at locations where wind projects are likely to be built in each region, determined based on the quality of the wind resource. While wind power data are scarce, wind speed data are abundant and readily available at reasonably high resolution throughout the United States. Near-surface hourly wind speed time series data can be scaled to reflect a typical turbine height, and then converted with the help of a "power curve"⁹ into corresponding simulated wind power output time series. We have attempted to perform a comparison of one of our simulated wind power time series with the output of a nearby physical wind-power project; however, the results are difficult to interpret. The wind power and the wind data are not from exactly the same location or height, and even such small differences can be extremely significant in determining the output of a resource. The technology and vintage represented by our power curve is also unlikely to be well matched to the actual technology and vintage of the specific wind turbines for which we have data. Even so, this approach provides a useful means of evaluating the potential impacts of wind energy production on emissions. The data sources and comparison results are described in more detail below.

Data Sources for Synthetic Generation

Over 1700 meteorological stations collect hourly data throughout the United States and territories for the National Climate Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA). Our primary source of wind data for generating synthetic wind power time series was NCDC's Weather Bureau Army Navy (WBAN) stations, distributed throughout the United States. To estimate the temporal characteristics of potential wind power generation, and thus expected indirect emissions reductions for each eGRID subregion, we needed to determine likely locations for new wind generation projects. We did this by reviewing the highest resolution available 50-meter wind speed estimates in each eGRID subregion, as cataloged by the NREL,¹⁰ to determine where favorable wind resources were likely to be located based on average wind speeds at 50-meter hub heights. We assumed that the minimum economic wind speed threshold for a wind power project would be at Class 4 wind speeds, or winds of

⁹ A "power curve" is a graph which relates wind speed to expected power production for a specific wind turbine technology and configuration. Actual power output data from wind turbines generally exhibit considerable scatter around the expected power curve, but this remains the best means of characterizing this relationship.

¹⁰ USDOE NREL Wind and Hydropower Electricity Program, 2007. Available online at: http://www.eere.energy.gov/windandhydro/windpoweringamerica/wind_maps.asp

15.7-16.8 miles per hour (mph). Once the area was selected in this manner, the closest high-quality NCDC station wind data location was selected for each subregion. Twenty-two NCDC meteorological stations near these locations were selected as proxies to represent the temporal pattern of wind generation expected at these sites. The locations of the sites and summary wind characteristics from the selected NCDC WBAN stations may be found in Appendix C.

It must be noted at the outset that the geographic granularity of the wind data is far from satisfactory. Wind conditions can change significantly over spatial scales as small as a few kilometers or less, so representing each eGRID subregion with a single site entails a considerable simplification. We have tried to choose sites which are reasonably representative of promising wind power locations for each region, understanding that considerably more research and analysis would be needed to pick a truly representative site, if indeed a single site can stand in for a large region. The same can be said for solid waste and landfill gas projects considered in our analysis: there is simply not enough information available to confidently predict the behavior of all potential future sites. This is an inevitable shortcoming of attempting to represent site-specific characteristics on a national scale, and it should be kept in mind by the reader in interpreting our results.

Generation of Synthetic Wind Power Data

WBAN meteorological stations are typically located at local and regional airports, or near rural towns, at 10 meters (33 ft) above ground level. Due to surface friction, wind speeds near the ground are significantly lower than speeds at expected 50-100 m windmill hub heights. In addition, the WBAN stations collect meteorological data in irregular intervals, with increments of approximately one hour. To create hourly synthetic time series, we used the simple average of the two measurements surrounding each hour. Next we normalized wind speeds to Class 4 speeds by scaling the time series for each station to an average speed of 16.25 mph, as follows:

$$WS_{i,j} = WS_{i,j}^0 * \frac{16.25}{\overline{WS}_j} \quad (1)$$

Where:

$WS_{i,j}$ = Adjusted wind speed during hour i and station j

$WS_{i,j}^0$ = Unadjusted wind speed during hour i and station j

and \overline{WS}_j = Average unadjusted wind speed at station j over all hours.

Wind scales non-linearly with height, increasing in speed as the influence of ground-level friction decreases. However, we assume that a proximal Class 4 wind site would have similar temporal characteristics to the meteorological station, and thus our approximation is to scale the WBAN wind data linearly to reflect Class 4 characteristics. This approach encompasses a host of decisions, design parameters, and operational characteristics into a single scalar that represents, roughly, the decisions made by the builder of a wind power facility to optimally exploit a local resource.

To convert the scaled wind data into synthetic wind power data, it was necessary to select a proxy technology with an appropriate wind power conversion function. We used a wind power curve based on the General Electric (GE) 1.5se (1.5 MW nameplate capacity) wind turbine to estimate potential generation associated with the wind time series at each selected meteorological station. The power curve, shown in Figure 2, is determined by a number of factors including the area swept by the blades, the “pitch” or angle of the blades (which can be variable in different wind conditions), and characteristics of the turbine gearbox. Wind turbines require a minimum amount of wind to begin generating power, known as the cut-in speed, and are designed to stall, or even brake, at higher wind velocities (the cut-out speed) to avoid damage.¹¹ Once again, we do not know a priori what technology or set of parameters would be most appropriate for a wind turbine in each area, but by scaling the winds to match a proxy turbine we generate a series that preserves temporal variability while representing a project which is optimized to local conditions.

Power Curve

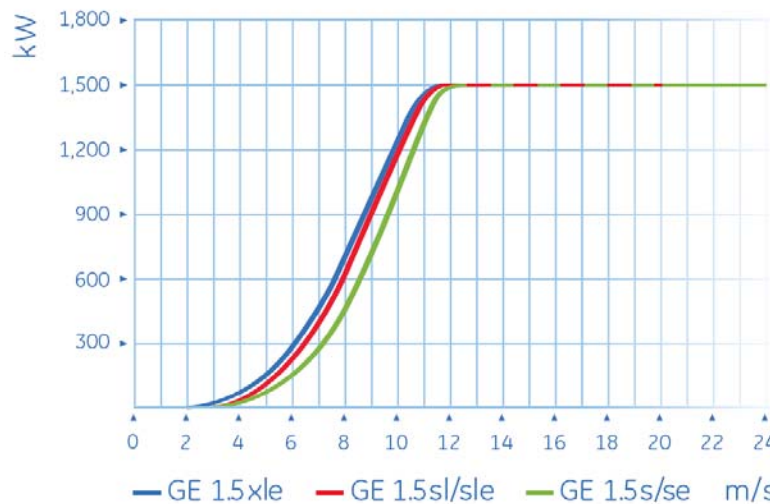


Figure 2. Wind power curve for a GE 1.5se (1.5 MW) wind turbine.

Source: http://www.gepower.com/prod_serv/products/wind_turbines/en/downloads/ge_15_brochure.pdf

The GE 1.5se proxy turbine is a common mid-sized turbine used on-shore; larger turbines are generally used offshore due to high wind conditions. The design tower height for these turbines is 54.7 meters (m), with 35.25 m blades sweeping an area of 3,904 m². The cut-in speed is 4 meters per second, and the cut-out speed is 25 meters per second. To generate the wind power time series, we relied upon a GE-supplied power curve which was imported as a look-up table for our analysis; the look-up table indexes the power curve and returns an estimated generation value for each hour given the calculated wind speed at turbine height.

¹¹ Tony Burton, David Sharpe, Nick Jenkins, Ervin Bossanyi, *Wind Energy Handbook*, John Wiley & Sons, 2001.

For purposes of our analysis, we approximated the GE wind power curve with a sigmoid function:

$$Q = \frac{a}{1 + e^{b-cWS}} \quad (2)$$

Where Q is output (kW) and WS is wind speed ($\text{m}\cdot\text{s}^{-1}$). The best fit to the GE curve in these units was obtained with parameter values $a=1500$, $b=8.1$, and $c=0.9$. The curve was truncated to zero at the cut-out speed of $25 \text{ m}\cdot\text{s}^{-1}$. The resulting curve is shown in Figure 3, along with reported and scaled wind data.

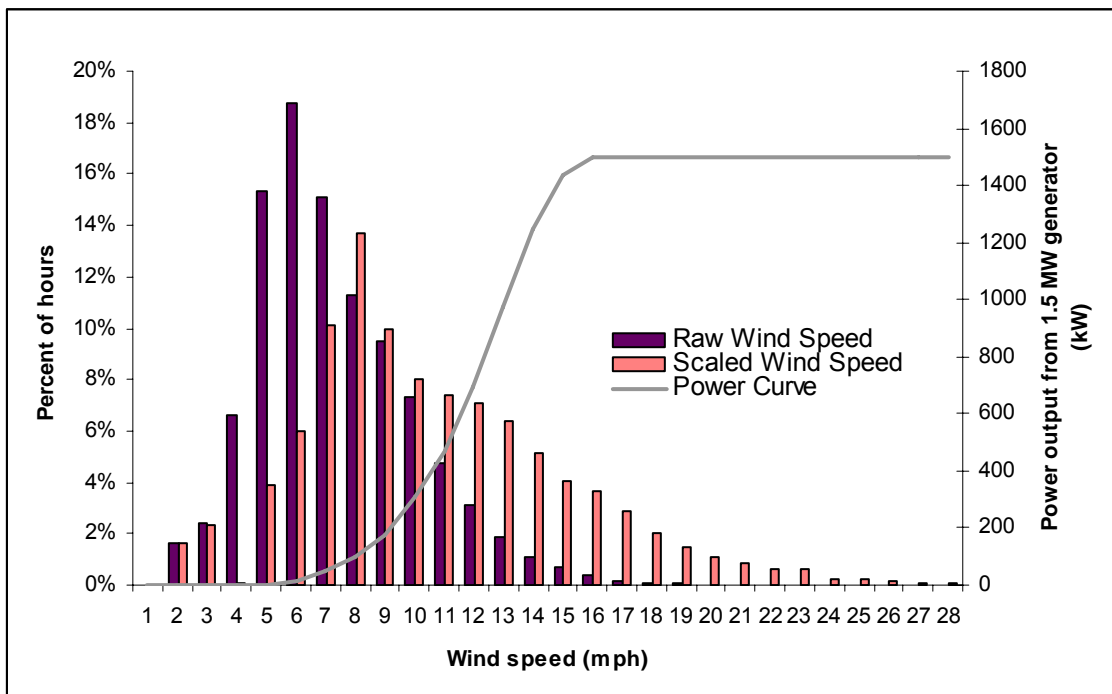


Figure 3. Proxy wind turbine power curve plotted against histograms of raw and scaled wind speeds at a sample site in the Midwest. “Scaled” wind speeds are adjusted to reflect class 4 winds at a turbine height of 50-100 meters using Equation 1.

Comparing Empirical and Simulated Wind Generation

As noted earlier, we were able to find one source of wind power data for comparison with our synthetic power profiles. The wind power time series that we were able to obtain represent twelve operational projects associated with the NREL wind farm monitoring program. The NREL data cover twelve sites including two in Minnesota, one in Iowa, one in Oklahoma, four in Texas, and four in Oregon. Total capacities ranged from 25 MW to 230 MW, and the turbines ranged from 0.6 to 1.6 MW each. While NREL was able to make 2005 production records from these projects available for research purposes, site-identifying information remains confidential. The turbines represent primarily plain and low-ridge wind farms; the farms in Iowa and Minnesota are distributed throughout active agricultural land, while the Oregon, Oklahoma, and Texas sites partially overlap grazing lands.

To test whether our simulated wind generation time series were realistic and representative of the output profile for a physical wind project at the same location, we selected an NREL wind project from a midwestern U.S. location and compared the recorded output with the simulated production time series generated using wind data from a nearby location. The test project is in a region with Class 4 and Class 5 wind speeds, running 145 turbines of 750 KW each, for a total capacity of 108 MW. A nearby WBAN meteorological station was located, and wind records for this location extracted from the NCDC data. The wind data were transformed through the power curve (Equation 2) to generate hourly power output.

Such a comparison has a number of complications, including:

- **Gaps in wind data.** In the case of the selected series, there are 84 gaps larger than 2 hours in duration, and 9 gaps longer than 24 hours in duration. The longest gap is nearly a week in duration. We have no way of knowing whether these were neglected because they were zero, or they were very high, or they simply represent random data errors, Thus it is impossible to determine what effect their omission may have on our analysis.
- **Gaps in power output data.** The output time series for the installed project has 552 missing hours in the sample year (6% of all hours) which were removed from the analysis. As with the missing wind data, it is impossible to determine what effect their omission may have on our analysis.
- **Granularity of wind data.** Wind speed data are taken approximately once per hour, meaning that variations in wind speed within each hour are unknown. In addition, the wind data show recording artifacts, such as certain values that rarely appear in the record including any measurements between approximately 0.5 and 2.75 mph. We have not attempted to perform any smoothing to compensate for this.
- **Representativeness of wind site.** While the wind data are taken from a meteorological station in proximity to the turbine, the station is clearly not measuring winds identical to those that drive the turbine. This lack of correspondence to actual values is exemplified by the average wind speed in the meteorological record of only 9.71 mph; to scale to the Class 4 average of 16.25 mph winds, we multiply all values by 1.67, consistent with Equation 1. In addition, a wind power installation can contain hundreds of turbines, each responding to highly localized conditions and each subject to maintenance schedules and other operational constraints which are not captured in the power curve.
- **Idealization of power curve transformation.** Each hour's scaled wind speed is transformed into an hour of power output assuming a perfect generator response to steady winds, neglecting any effects such as generator inertia which may dampen the response. Wind speeds are implicitly assumed to hold steady for exactly one hour before instantly changing to the next hour's value, again with an instantaneous response from the turbine.

The comparison of simulated and observed power output is shown in Figure 4. In this analysis we take the maximum recorded output for the year as the maximum output for the station, although this value is only about 90% of the nameplate capacity of the

installation. This assumption presumably corrects for scheduled maintenance and forced outages which would affect some subset of turbines at all times.

The simulated output curve shows an exaggerated peak at 5%-10% of capacity relative to the recorded power output series, and a peak at the 100% output level which is absent in the observed data. These peaks likely reflect the granularity issues identified above for the wind records, which can reflect just one or two observations for each hour while the measured power output reflects inevitable variations in wind speed and output over the course of each hour. For the simulated project the overall capacity factor over the course of the study period is 32.8%, while for the observed project the overall capacity factor is 30.3%.

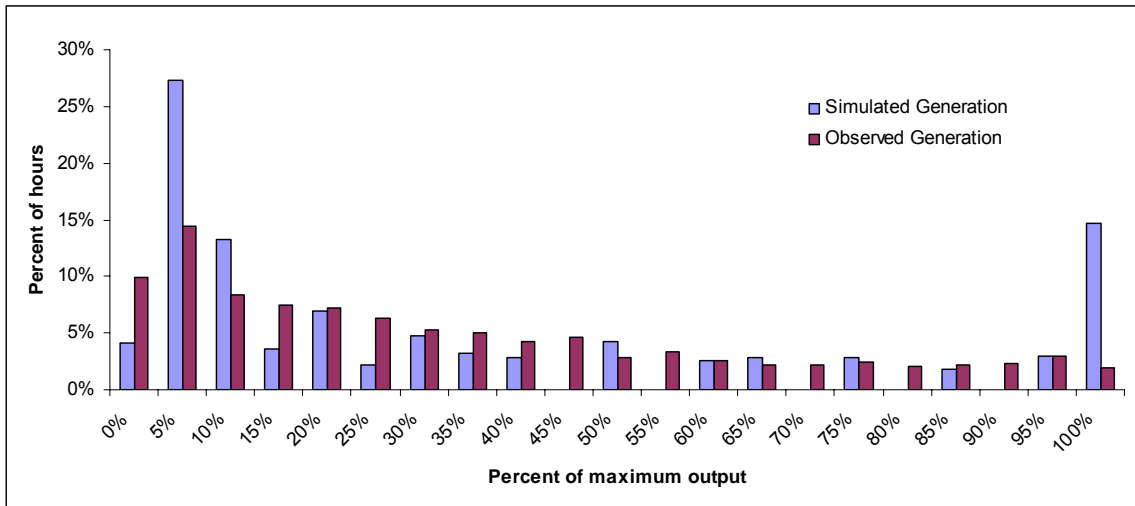


Figure 4. Comparison of power output distribution at sample wind power site in the Midwest with predicted output based on scaled wind data from a nearby meteorological station. Output levels for observed generation are relative to the maximum recorded output for the year.

The simulated and observed generation, as well as the difference between the two, are shown on color charts in Figure 5. These charts represent each hour of the year as a cell on a 24-hour by 365-day matrix, with each cell color-coded according the scheme shown. Figure 6 shows a cumulative distribution of the hourly deviation between the two, in percentage points. The simulated output exhibits a pronounced diurnal cycle which is not present in the project data. This discrepancy could be due to any number of factors, including light winds which blow through the evening at hub-heights which do not appear in the NCDC dataset (NCDC does not record wind speeds less than 3 mph at ground level) or more sensitive wind turbines with lower stalling speeds than the proxy turbine, which would produce a generally flatter distribution of power generation throughout the day. This discrepancy may also simply reflect the difference in the location of the two sites. The two time series are within 20 percentage points of each other during approximately 65% of the 6,434 hours recorded in both datasets.

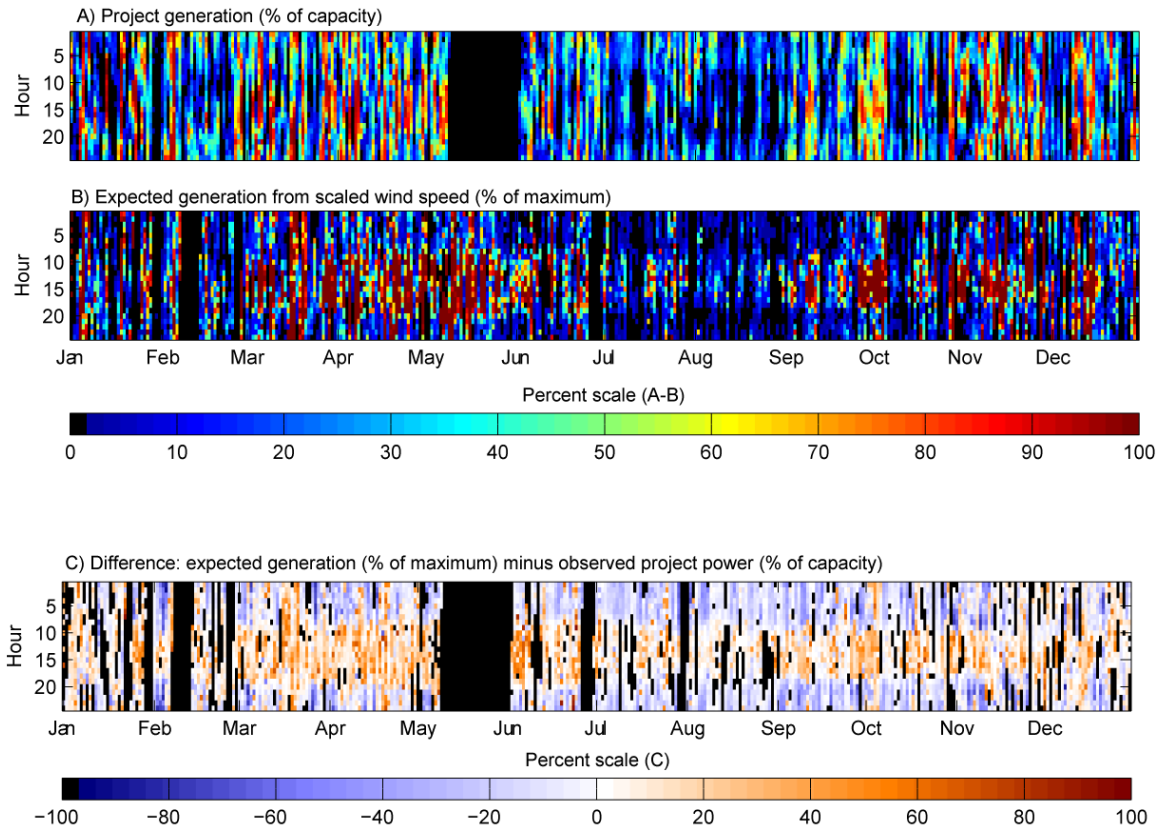


Figure 5. Comparison of hourly synthetic and observed wind power time series at nearby locations in the Midwest. Each plot shows 8,760 hours in 2005, with hour of the day on the vertical axis and day of the year on the horizontal. Missing data shown in black. *Top*: Observed wind power output (% of maximum); *Middle*: Synthetic wind power output (% of capacity) based on scaled wind speed data; *Bottom*: Hourly deviation of synthetic from observed time series.

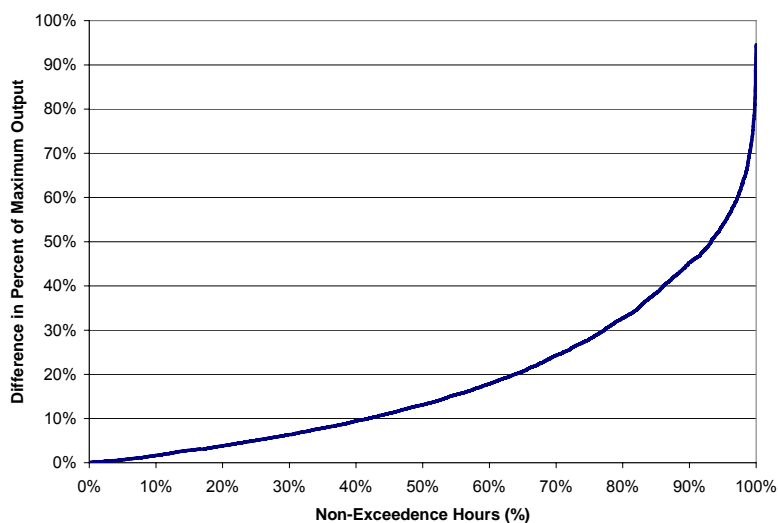


Figure 6. Cumulative distribution of the hourly deviation (in absolute percentage points relative to maximum output) between observed and synthetic generation time series.

While there are clearly significant discrepancies between these two datasets, we feel that the NCDC meteorological dataset is a reasonable, if by no means ideal, resource for estimating temporal patterns and potential offsets from projects which might be built in each eGRID region.

The hourly synthetic output generated for each of the eGRID subregions is shown in Appendix B as 24-hour by 365-day color intensity plots. Monthly summary tables of raw and scaled wind speeds, as well as synthetic wind power, may be found in Appendix C. The hourly data are available in electronic format upon request.

B. Landfill Gas

To determine the operational and dispatch characteristics of landfill-gas-fired generating facilities, we contacted several landfill gas (LFG) project developers.¹² We received hourly generation data for several landfill gas projects from Granger Electric Company and Granger Energy, LLC, (“Granger”) which together own and operate six landfill gas projects in Michigan, and 10 LFG projects in Indiana, Ohio, and Pennsylvania.

According to Granger, the generation profile of LFG projects generally does not differ significantly by time or season.¹³ The primary factors that impact the energy output of LFG projects have to do with ambient conditions. The warmer and the wetter the climate, the higher the methane content of the landfill gas, such that more power can be produced from this resource.

High temperatures also affect the plant’s output by generally reducing the temperature gradient that drives the turbine. This temperature effect is minimal for the reciprocating engines which are used by Granger. Gas turbines appear to be the predominant choice for LFG projects by other companies. Gas turbine outputs are more susceptible to variation in temperature. This characteristic largely mirrors the behavior of base load generating plants, and system operators can reasonably expect a constant and predictable stream of energy output from these facilities. Thus we conclude that the fossil-fuel-fired generation displaced by landfill gas in any region of the country will be similar in operational and emissions characteristics to typical base load resources in that same region.

C. Municipal Solid Waste

Municipal Solid Waste (MSW) generators, also known as waste-to-energy facilities, are currently operating in 27 states and burning roughly 95,000 tons of garbage each day, generating roughly 2.5 GW of electricity.^{14,15} Even with this large volume of output, the

¹² Landfill gas project operators were identified by Rachel Goldstein of the EPA Landfill Methane Outreach Program: <http://www.epa.gov/lmop/>.

¹³ Granger does have one project which operates as peaking generation, but this appears to be an anomaly and does not affect our conclusions about general LFG generation characteristics.

¹⁴ New York State Department of Environmental Conservation, <http://www.dec.ny.gov/chemical/8979.html>.

¹⁵ Because some portion of the fuel supply for MSW generators is generally fossil-based, there is some dispute over whether this resource should be considered “renewable” or not. However, as a number of state programs include MSW as a renewable energy source (see dsireusa.org for updated details), we treat it as a renewable resource for the purposes of this report.

facilities are not fuel-limited; our research and discussions with facility operators reveals that waste-to-energy plants run at high capacity factors of 85% and above. As with landfill gas projects, these characteristics suggest that they serve as base load capacity, and that the fossil generation they are likely to displace is also base load capacity. Thus we conclude that the fossil generation displaced by MSW in any region of the country will be similar in operational and emissions characteristics to typical base load resources in that same region.

3. Hourly generation and emissions data

In this section we characterize the operational, dispatch, and emissions characteristics of conventional power plants in order to predict the change in dispatch and emissions resulting from the presence of new renewable energy resources.

Electricity grids are often characterized as having a range of resource types including base load, intermediate, and peaking resources. These resources respond differently to variations in load over different timescales: put simply, base load resources run most hours regardless of load levels, intermediate resources ramp up and down frequently in response to changes in system load, while peaking resources run only during the highest load periods. However, real-world electric grids are more complicated than this, and real-world resources have complex operating constraints and practices depending on factors including heat rate, ramping capability, demand and price in the energy and ancillary service markets, availability of competing resources, local transmission constraints, environmental constraints, operator or dispatcher discretion, and even the warrantee and/or service contracts on specific pieces of generating equipment. It is thus impossible to predict with specificity which resources would respond to perturbations in load or available low-cost energy. However, historical data on unit operations can lend insight into which units are more or less likely to be displaceable at any point in time.¹⁶ To the extent that these operational data are coupled with emissions characteristics, they can be used to estimate the likely displaceable emissions at any point during a historical year. Such an approach would be more refined than using a simple average emission rate at any point in time to represent displaceable emissions, because it would be more sensitive to the actual dispatch characteristics of individual generating plants.

To implement this approach, we obtained generation and emissions data for United States fossil-fuel powered generating plants for 2005 from the Hourly Emissions database of the EPA Clean Air Markets Programs.¹⁷ The database consists of hourly reported generation, heat rate, and total emissions of CO₂, SO₂, NO_x, and mercury for all fossil fuel-fired generators with nameplate capacities above 15 MW. These data form the basis of all of the displaceable emissions analysis reported here. We use the hourly

¹⁶ It is common to think of generating resources as responding only to changes in electricity demand; however, certain intermittent renewable resources, such as wind generation, change the load on fossil resources in a very similar manner to variations in load. Thus we treat the availability of energy from such resources in the same manner that we would a reduction in energy demand from consumers.

¹⁷ EPA, 2007. Data Sets and Published Reports: Emissions Data Prepackaged Data Sets. Online at <http://camddataandmaps.epa.gov/gdm/index.cfm?fuseaction=prepackaged.select>

generation data to characterize the operational characteristics of generating units in each NERC subregion, and we use the associated emissions data to characterize the indirect emissions benefit that would be associated with displacing the output of each generating unit.

Characterization of emission rates

Hourly emissions are reported in the Clean Air Markets database for CO₂, NO_x, and SO₂. Within the database, the data records include fields to indicate whether the reported emissions are measured or calculated. Calculated emissions are based on the composition of the fuel, the unit's heat rate, and the output of the unit. In general, it appears that most of the emissions data in the database for 2005 are measured.

Pollutant emission rates are reported in the hourly emissions database as tons per million British thermal units (mmBtu) for CO₂, and pounds per mmBtu for NO_x and SO₂. For the purposes of this analysis it is necessary to consider emissions in units of mass per MWh output. However, while emission rates per unit of heat input may be fairly constant, emission rates per unit of energy output can vary considerably—this variation is due to changes in the efficiency (or “heat rate”) of a generating unit with different output levels. For purposes of this analysis, we will use the overall average emissions rate for each unit as derived from the EPA hourly emissions database, unless otherwise noted.

Data filtering

The EPA emissions data contain anomalous features which are indicative of either reporting or calculation errors. While the hourly generation data are used to characterize generator behavior and identify times at which the generator is operational, emission rates could be misleading if anomalous data were included. Therefore, data are removed from the emission rate analysis according to the following rules:

- Generation, CO₂, or heat rate is reported as zero.
- The reported heat rate is in the top 99.5th or bottom 0.5th percentile (for a record with 8,760 non-zero hourly values, this would remove the 44 highest and 44 lowest values).
- CO₂ emission rate is above 2.5 tons of CO₂ per megawatt-hour (tCO₂ MWh⁻¹) or less than zero.

We did not filter on the basis of NO_x or SO₂ measurements as we had no basis for judging reasonable emission rate limits.

4. Emissions Displacement Methods

In order to calculate the indirect emissions benefits associated with power production from renewable resources, it is necessary to determine which power plants will have their output curtailed as a result of the availability of the new resource. This need arises from the recognition that the emission rates of power plants which will be running in either case (with and without the new resource) do not affect the calculation; nor do those of power plants that would not be running in either case. In fact, it is only a small number of plants, as few as one marginal resource in any given dispatch interval, that will determine the relevant emission rate. The difficulty comes in identifying which plant or plants to consider, and thus in identifying the appropriate emissions rate or rates for each interval.

There are numerous factors that affect which power plants operate, are committed to operate, or are held in reserve at any point in time. These factors include:

- Offer price or short-run marginal cost;
- Constraints such as ramp rates, minimum up and down times, and other operating restrictions;
- Transmission or other dispatch constraints;
- Maintenance schedules;
- Unplanned outages and/or deratings; and
- Environmental constraints.

Unfortunately, most of this information is not available from public sources for most resources. Using only the information which we have available from the EPA database (i.e., hourly generation, heat rate, and emissions), it is impossible to reconstruct all of the factors that guide dispatch and to determine the precise marginal emissions rate in effect for any particular hour.

Our solution is to infer operational characteristics from the suite of units in each region based on their patterns of operation and emissions over the course of the study year. There is a broad range of possible approaches to interpreting the data in this manner. Some of these approaches use emissions characteristics aggregated over a season or year, and some are more directly focused on hourly analysis.¹⁸ Each approach carries its own implicit model about system operation and response to new resources, and each may be more appropriate than others to address the impact of certain kinds of resources or over specific time scales. In this analysis, we present five methods, ranging in simplicity, design, and conceptual model, and explore the implications of each. These methods are:

¹⁸ Earlier investigations based on extracting hourly performance information from the same EPA database used here:

- Connors, S., K. Martin, M. Adams, E. Kern, and B. Asiamah-Adjei. 2005. "Emissions Reductions from Solar Photovoltaic (PV) Systems" Publication MIT LFEE 2004-003 Report.
- Berlinski, M. and S. Connors, "Economic and Environmental Performance of Potential Northeast Offshore Wind Energy Resources: Final Report", Report to the Offshore Wind Collaborative Pilot Research Projects, January 2006.

- Hourly Average Emissions Rate (HAER);
- Annual (and seasonal) emissions slope factor (Slope Factor);
- Empirical Incremental Emissions Rate (EIER);
- Load-Following Rate Incremental Emissions Rate (LFIR); and
- Flexibility-Weighted Hourly Average Emissions Rate (FW-HAER).

A. Limiting Cases

Before delving into each method in detail, it is useful to characterize the most extreme emission scenarios to bound the results of our analysis, particularly with respect to CO₂. In producing a single MWh of electricity, power plants fueled by coal (the most carbon-intensive fossil fuel) typically produce somewhat over one ton of CO₂; modern plants fueled by natural gas produce about 0.6 tons of CO₂ per MWh.¹⁹ The exact emission rate for each plant depends on technology, age, maintenance, and specific fuel (i.e., some coals have a higher carbon content than others for the same energy output.) The ranges of reported hourly emission rates for gas, coal, and oil-fired plants in the EPA database are shown in Figure 7. While this figure highlights some of the anomalous data in the database, such as coal plants which report unrealistically low CO₂ emissions, it does show that the reported data are generally consistent with the expected range of emission rates by fuel type.

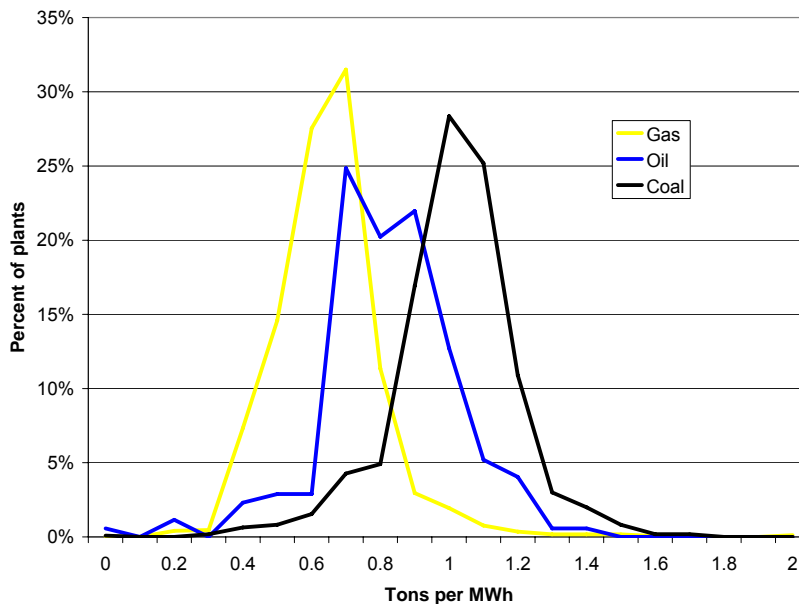


Figure 7. Distribution of CO₂ emission rates for fossil generating plants by reported fuel type. Note that reported primary fuel is not a precise categorization, as some units are capable of switching fuels and some plants may actually have units which burn different primary fuels.

The difference between emission rates from coal and gas essentially bounds the range of outcomes in accounting for the displaced emissions associated with renewable

¹⁹ http://www.eia.doe.gov/cneaf/electricity/page/co2_report/co2emiss.pdf. Values in the EPA database confirm these numbers: the median emission rate for a coal plant is 1.024 tCO₂ MW⁻¹, while for a gas plant it is 0.697 tCO₂ MW⁻¹

generation. Renewable resources cannot displace more carbon emissions than the emission rate of an inefficient coal plant on a per-MWh basis; nor is it likely that they will displace less CO₂ for each MWh generated than the amount emitted by an efficient combined cycle gas plant. This is because other low-carbon sources of power (such as nuclear and hydro) have low running costs and are unlikely to be displaced.^{20,21} In general, the result will lie somewhere between these two extremes.

For NO_x, the story is somewhat more complicated. NO_x emissions tend to be bifurcated into ozone-season emissions (May through September), when emissions are regulated and many power plants are operating emissions control technology; and non-ozone season emissions, when they are not. As will be shown below, in some areas this bifurcation is more pronounced than in others. However, NO_x emission rates generally range from zero to perhaps five or six pounds per MWh, with ozone season rates generally one or two pounds below non-ozone season rates.

SO₂ emission rates depend upon the fuel used for generation, with natural gas having no sulfur (and therefore producing no SO₂) and certain types of coal having the most. Thus if only gas generation is displaced, there is no displacement of SO₂ emissions. For this reason, we would expect SO₂ to have perhaps the largest regional displaceable emissions differences of all of the pollutants considered, with ranges from zero up to about eight pounds per MWh for regions that rely on coal resources for load following capacity.

To narrow these ranges, it is necessary to find a means to identify which types of plants are more likely to be displaced in any given region. All of the methods described in this section are designed to refine the estimate of displaced emissions based on the observed operational characteristics of the system as deduced from the EPA database.

For clarity, we will develop the displacement methodologies with primary reference to carbon dioxide emissions since it is the primary anthropogenic cause of global warming. However, results will be presented for all three of the pollutants considered here.

B. Hourly Average Emissions Rate (HAER)

One of the most conceptually straightforward methods for estimating displaced emissions is to use a simple hourly average. This method calls for adding the aggregate emissions from an eGRID subregion (for example, in tCO₂) for each hour of the study period and dividing this by aggregate fossil generation (MWh) for the same hour:

$$HAER_t = \frac{\sum CO_2(t)}{\sum MW(t)} \quad (3)$$

²⁰ As noted earlier, displaced emissions are not necessarily equivalent to avoided emissions, as emissions policies and other factors can come into play in determining total emissions in any given area.

²¹ There are exceptions to this statement – in some cases storage hydropower may be the most flexible resource available to follow load. However, storage hydro is energy-limited resource, so total generation from such a facility will not be affected by the presence of a new renewable resource.

Where t denotes a particular hour, and the summations are over all of the generating units in the region of interest.

Equation 3 produces the average emissions rate across all fossil units for a specific region and hour, with the implicit assumption that every fossil plant running during that hour has an equal probability of being displaced. This is clearly not the case on an hour-to-hour basis: certain units have limited ramping capability and other operational and economic constraints which dictate that they only be used as base load resources. However, this method is fairly straightforward to understand and apply, and as noted earlier we cannot know for sure which units would be displaced in any hour. In addition, as the market matures with higher levels of renewables penetration, it is reasonable to imagine that units throughout the supply curve may ultimately be displaced. Finally, this method may be the most appropriate for base load renewables such as landfill gas or municipal solid waste combustion, for which output is stable and predictable. Thus it may be reasonable to quantify displaced emissions using this approach if more of a long-term or base load impact is under consideration for any of these reasons.

Figure 8 shows selected representations of the variations in HAER for CO₂ in the New England (NEWE) eGRID subregion. The first representation is a timeline of hourly variations, demonstrating that the CO₂ emissions rate fluctuates between about 0.65 and 0.95 tCO₂ per MWh, with an average of 0.73 tCO₂/MWh and a standard deviation of 0.05 tCO₂/MWh. The second panel from the top shows a three-week period in the summer in more detail. The second representation (third from top) is a histogram of hourly HAER values. The final representation (bottom panel) recasts the dataset as a color intensity image of HAER, with day of year (DOY) in 2005 along the horizontal and the hour of the day on the vertical. The green / yellow band across the top and bottom of the image indicates that the evening hours have higher average emission rates, probably reflecting the lower contribution of natural gas units during these hours.

We can see from these graphs that there is significant diurnal variability to the data over a fairly narrow range, with higher hourly average emission rates at night. This reflects the low position in merit order for coal plants with higher CO₂ rates, which dominate the lower-usage hours at night, but also the fact that these same large plants strongly influence the overall average, in combination with lower-emitting gas plants, even during peak times.

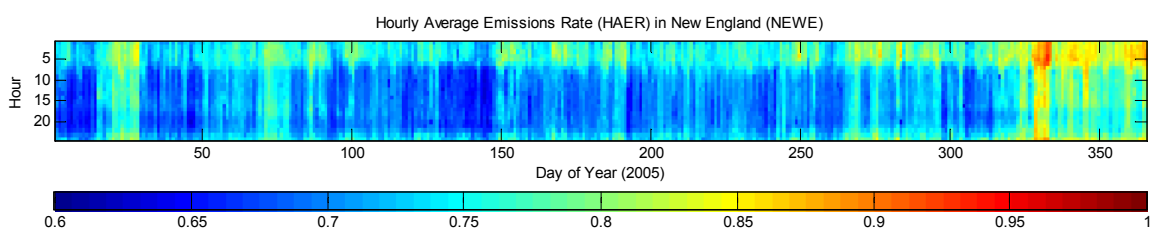
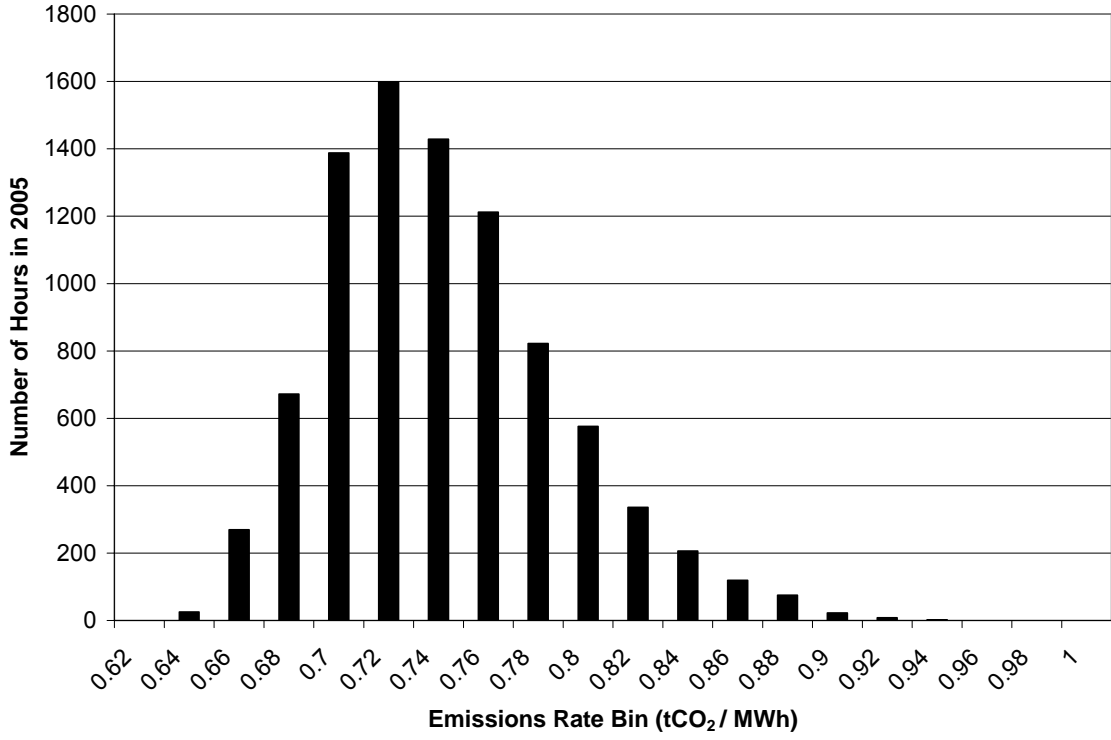
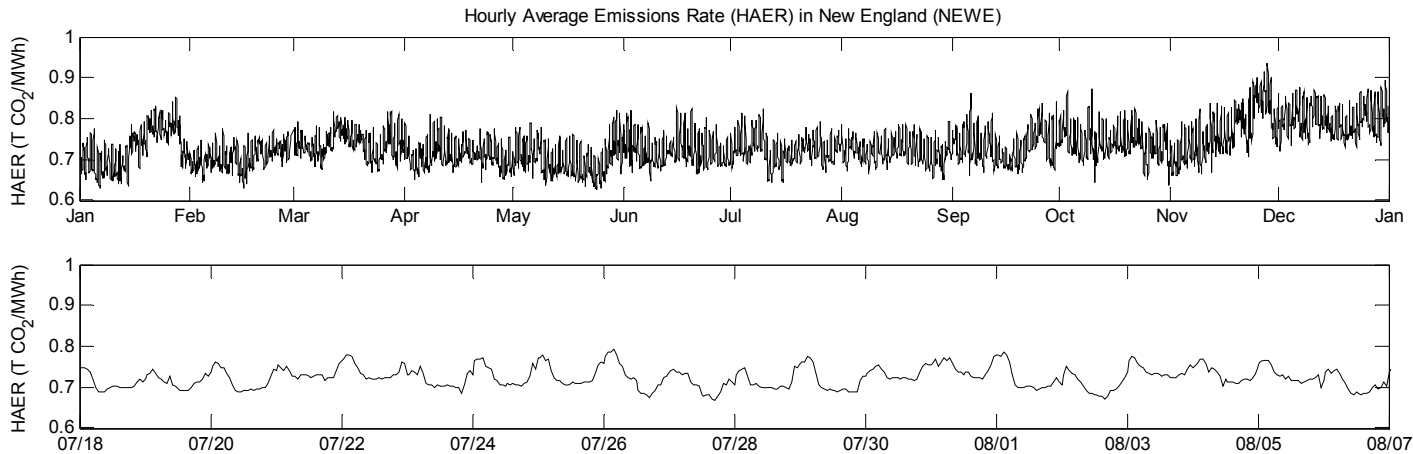


Figure 8. Representations of CO₂ Hourly Average Emissions Rate (HAER) in New England. Top: full record, with detail shown for three weeks in the summer of 2005; Middle: Histogram of hourly emissions rates showing distribution throughout the year; Bottom: 24x365 color representation of emission rates, showing diurnal cycle and seasonal variations.

C. Emissions Slope Factor

The emissions slope factor is an empirical estimate of the marginal emissions rate based on the assumption that the observed linear relationship between emissions and electricity output from fossil fuel units is the best indicator of the system's response to a change in load. This factor can be calculated as a simple regression relationship over an entire year, or on a seasonal basis. Because of seasonal differences in dispatch and operating constraints, there may be additional value in performing this analysis on a seasonal basis. For the time period under consideration, total emissions and total fossil generation for each subregion are summed for each hour, based on the EPA database. When the hourly pairs of emissions/output data points for a subregion are plotted on a scatter plot, the slope of the regression line represents an empirical measure of the dependence of emissions on total electricity output in units of mass of pollutant emitted per MWh produced. If the correlation is high, this slope provides a reasonable estimate of the regional, seasonal avoidable emissions factor for a change in load or for the addition of emissions-free energy. This metric makes no specific assumptions about which generator will be displaced by a change in system load, but instead relies on a robust diagnostic of the overall system response to variations in load.

One interesting feature of this approach is that the line of best fit rarely has a y-intercept of zero. This may seem counterintuitive, as zero generation would surely be associated with zero emissions. However, zero generation is clearly a domain which is not of interest for this analysis, and the very lowest generating units on the supply curve are likely to have emissions characteristics that diverge from those of units that are more likely to be load-following. Were we to force the regression lines to cross through the origin, we would obtain a much poorer estimate of the emission factor in each region.

Figure 9 illustrates the application of this method for emissions in the Reliability First/Central (RFCE) subregion. All three pollutants of interest are shown. CO₂ and SO₂ emissions can be characterized as having a linear dependence on total MW output, with R² values of 0.98 and 0.81, respectively.

The NO_x emissions data (Figure 10) do not lend themselves to this simple relationship. Readily apparent from the Figure are two different trends. These trends represent the emissions in the ozone season, when most generating units are required to operate ozone control technology, and the non-ozone season when they are not.²² Finally, there appears to be an up-tick in NO_x emissions during very high load hours during the ozone season. This up-tick may represent units that disengage their NO_x controls to increase output during very high load hours.

²² Complicating this analysis is the fact that many units were not required to report NO_x output during the non-ozone season in 2005.

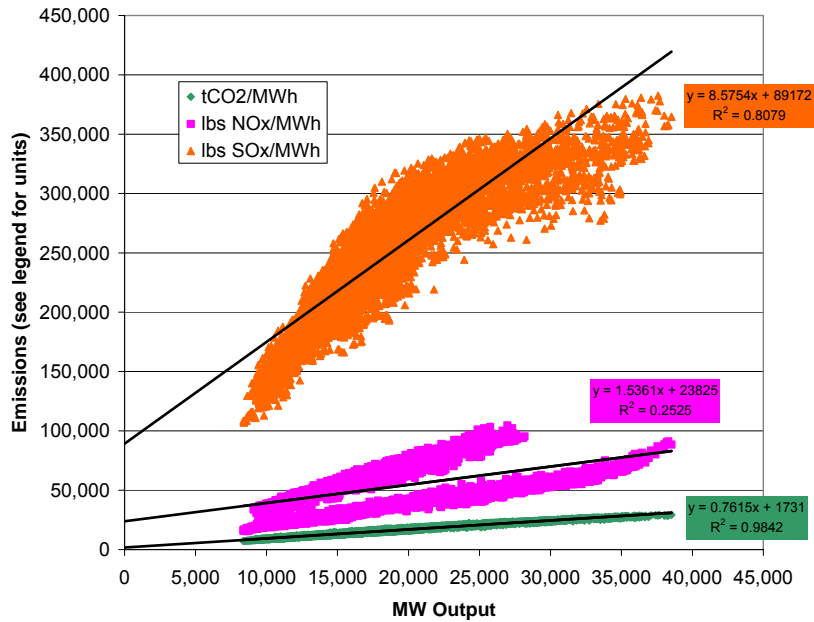


Figure 9. Determination of the regional Emissions Slope Factor in the RFCE (Reliability First/Central) region. Total emissions of CO₂, NO_x and SO₂ vs. MW output for each hour of 2005 are shown. A linear line of best fit is calculated for each pollutant, and the slope of this fit determines the annual slope factor for the region. The bifurcation of the NO_x data reflects the differential operations of pollution control equipment during the ozone (summer) vs. non-ozone seasons.

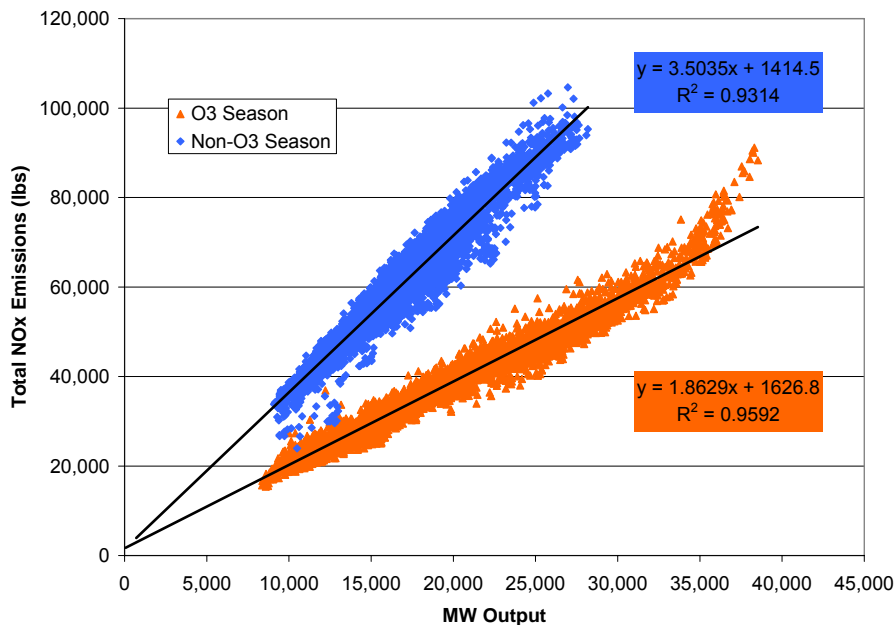


Figure 10. Bifurcation of the NO_x emissions slope factor (pounds of NO_x per MW output) for the RFCE region. Slopes for the ozone season (May through September) and non-ozone season hours are shown. The difference reflects the required operation of ozone control technology during the ozone season. Also apparent are excess NO_x emissions during high-load hours during the ozone season.

These figures and statistics suggest that the empirical slope factor approach is a well-defined and reasonable way to characterize the variation of emissions with load in this region, especially if some care is taken in subdividing the load to isolate meaningful trends. Unfortunately, the regression relationships are not as constrained for all pollutants and all regions. Figure 1 shows the seasonal and annual slope factors for CO₂, and Table 2 for SO₂, for each eGRID region. Table 3 shows analogous results for NO_x separated into the ozone and non-ozone seasons. Also shown are the corresponding R-squared metrics indicating the strength of the regression relationship underlying each slope factor. The R-squared values for CO₂ are uniformly quite high, indicating strong confidence in these calculated slopes. For NO_x the relationships are also generally quite strong, but for SO₂ the relationships range from very strong to extremely weak. This diagnostic should be taken into account in applying this approach.

In most cases, the differences between the seasons are small, and some of these relationships require significant error bars. As a rule we apply seasonal slopes in performing the emissions analysis, but it is important to keep in mind that we do so with more confidence in some areas and for some pollutants than for others.

Summary results for the Slope Factor method for all eGRID subregions, including factors calculated for CO₂ (tons/MWh), SO₂ (lbs/MWh), and NO_x (lbs/MWh) are displayed in Figure 11, Figure 12, and Figure 13, respectively.

Table 1. Seasonal and annual emissions slope factors (left) and R-squared values (right) for CO₂. Spring = March-May; Summer = July-August; Fall = September-November; Winter = January, February, and December.

Region	CO ₂ Slope Factor					R-Squared				
	Spring	Summer	Fall	Winter	Annual	Spring	Summer	Fall	Winter	Annual
AZNM	0.59	0.53	0.56	0.55	0.58	0.95	0.97	0.94	0.91	0.96
CAMX	0.56	0.50	0.53	0.48	0.52	0.91	0.99	0.95	0.92	0.97
ERCT	0.69	0.59	0.64	0.67	0.66	0.94	0.99	0.99	0.97	0.97
FRCC	0.73	0.69	0.73	0.72	0.74	0.98	0.99	0.99	0.99	0.99
MROE	0.80	0.77	0.83	0.96	0.83	0.94	0.97	0.95	0.94	0.95
MROW	0.97	0.88	0.93	0.91	0.95	0.98	0.99	0.98	0.94	0.98
NEWE	0.63	0.65	0.61	0.68	0.65	0.94	0.98	0.97	0.88	0.95
NWPP	0.82	0.71	0.78	0.70	0.82	0.97	0.95	0.90	0.87	0.95
NYCW	0.66	0.55	0.63	0.64	0.56	0.83	0.97	0.98	0.91	0.93
NYLI	0.55	0.48	0.61	0.51	0.53	0.84	0.90	0.97	0.82	0.92
NYUP	0.69	0.66	0.60	0.76	0.66	0.95	0.97	0.92	0.95	0.95
RFCE	0.78	0.69	0.75	0.81	0.76	0.99	0.99	0.98	0.98	0.98
RFCM	0.81	0.67	0.75	0.93	0.71	0.81	0.97	0.91	0.94	0.93
RFCW	0.95	0.85	0.89	0.92	0.89	0.98	0.99	0.99	0.99	0.99
RMPA	0.74	0.70	0.86	0.89	0.79	0.85	0.92	0.90	0.93	0.90
SPNO	0.93	0.93	0.96	1.08	0.97	0.94	0.97	0.99	0.97	0.97
SPSO	0.70	0.60	0.66	0.65	0.66	0.87	0.98	0.97	0.89	0.94
SRMV	0.66	0.60	0.64	0.64	0.61	0.94	0.97	0.94	0.89	0.96
SRMW	0.93	0.86	0.95	0.99	0.94	0.99	0.99	0.99	0.98	0.99
SRSO	0.83	0.70	0.79	0.80	0.80	0.99	0.98	0.97	0.96	0.98
SRTV	0.81	0.76	0.87	0.88	0.84	0.97	0.97	0.98	0.97	0.97
SRVC	0.94	0.79	0.88	0.90	0.85	0.97	0.99	0.98	0.99	0.98

Table 2. Seasonal and annual emissions slope factors (left) and R-squared values (right) for SO₂.

Region	SO ₂ Slope Factor					R-Squared				
	Spring	Summer	Fall	Winter	Annual	Spring	Summer	Fall	Winter	Annual
AZNM	0.29	0.19	0.34	0.07	0.06	0.06	0.10	0.11	0.00	0.00
CAMX	0.31	0.03	0.33	0.16	0.18	0.05	0.01	0.10	0.03	0.07
ERCT	1.49	0.51	0.80	1.52	0.86	0.32	0.16	0.26	0.27	0.25
FRCC	5.68	5.08	5.30	5.70	5.19	0.94	0.92	0.93	0.79	0.91
MROE	4.65	3.59	4.18	6.20	4.15	0.70	0.68	0.34	0.79	0.47
MROW	6.59	4.36	5.06	5.22	4.95	0.82	0.82	0.75	0.74	0.80
NEWE	3.04	3.26	1.87	4.33	2.98	0.38	0.78	0.27	0.63	0.40
NWPP	2.15	1.07	1.25	0.97	1.85	0.74	0.28	0.09	0.05	0.47
NYCW	1.51	1.01	1.35	2.07	0.99	0.47	0.70	0.77	0.83	0.51
NYLI	2.94	1.59	3.01	3.05	2.07	0.33	0.54	0.75	0.55	0.50
NYUP	6.11	5.98	4.93	7.00	6.14	0.84	0.88	0.76	0.79	0.85
RFCE	12.99	6.39	8.58	9.73	8.58	0.87	0.79	0.78	0.85	0.81
RFCM	7.40	4.77	6.85	9.68	5.87	0.72	0.78	0.79	0.72	0.72
RFCW	13.66	10.38	12.02	14.73	11.00	0.76	0.90	0.92	0.93	0.84
RMPA	0.06	1.00	2.03	0.82	1.11	0.00	0.19	0.49	0.15	0.19
SPNO	5.91	7.02	7.84	7.26	6.59	0.45	0.85	0.90	0.79	0.79
SPSO	1.52	1.03	1.52	2.13	1.43	0.21	0.43	0.53	0.41	0.38
SRMV	1.41	1.53	1.53	1.91	1.52	0.35	0.62	0.32	0.36	0.47
SRMW	6.69	6.58	6.64	9.02	7.08	0.72	0.83	0.89	0.70	0.79
SRSO	8.75	5.26	7.28	9.14	7.57	0.81	0.64	0.67	0.75	0.77
SRTV	6.56	6.36	7.19	9.23	7.07	0.45	0.70	0.72	0.72	0.66
SRVC	10.84	7.29	9.76	10.24	8.60	0.90	0.89	0.90	0.92	0.89

Table 3. Ozone season and Non-Ozone season emissions rate slopes for NOx. Ozone season = May through September.

Region	NOx Slope Factor		R-Squared	
	Ozone season	Non-Ozone Season	Ozone season	Non-Ozone Season
AZNM	0.79	0.92	0.54	0.28
CAMX	0.20	0.62	0.21	0.42
ERCT	0.83	0.76	0.88	0.59
FRCC	2.56	2.63	0.95	0.90
MORE	1.37	1.93	0.77	0.64
MROW	3.26	4.43	0.90	0.85
NEWE	1.10	1.34	0.83	0.52
NWPP	2.17	2.37	0.88	0.61
NYCW	2.08	1.70	0.89	0.52
NYLI	1.88	2.24	0.82	0.74
NYUP	1.61	2.15	0.93	0.82
RFCE	1.86	3.50	0.96	0.93
RFCM	2.06	3.29	0.87	0.71
RFCW	2.10	5.18	0.95	0.87
RMPA	1.73	2.61	0.55	0.67
SPNO	4.06	5.56	0.88	0.85
SPSO	2.21	2.58	0.94	0.74
SRMV	1.68	1.51	0.71	0.66
SRMW	1.17	3.55	0.50	0.67
SRSO	1.40	2.26	0.80	0.67
SRTV	1.80	4.38	0.77	0.73
SRVC	1.61	3.60	0.96	0.90

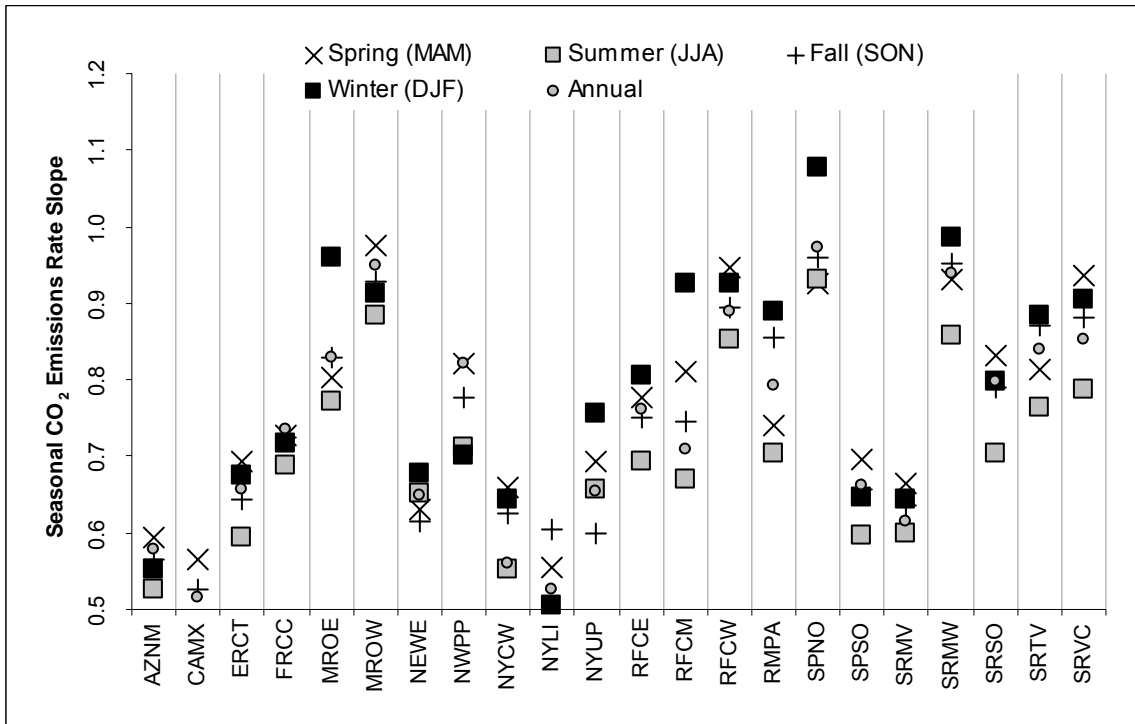


Figure 11. Regional slope factors for CO₂ (tons/MWh)

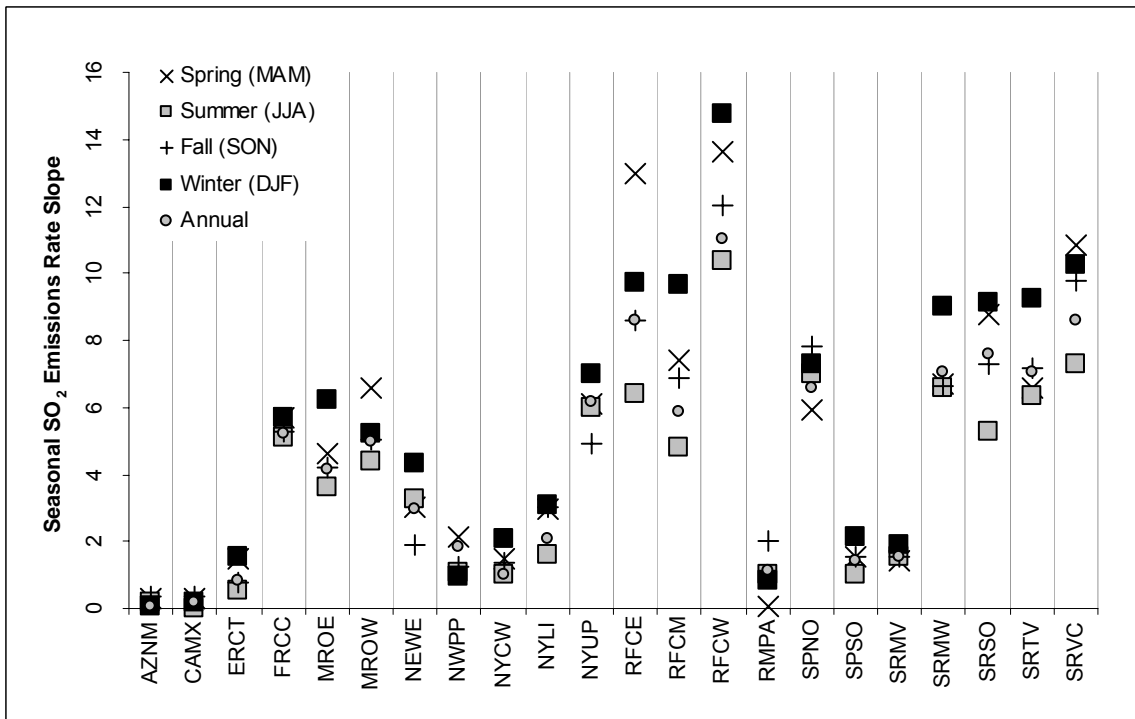


Figure 12. Seasonal and regional slope factors for SO₂ (lbs/MWh)

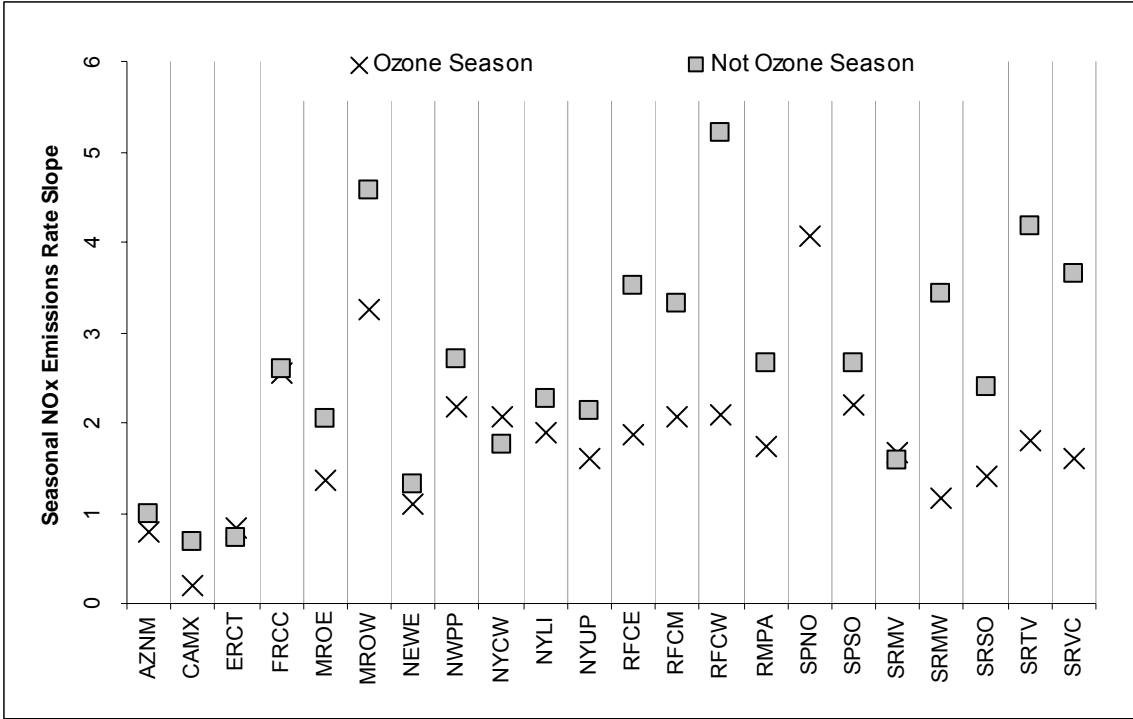


Figure 13. Regional slope factors for NOx (lbs/MWh)

D. Empirical Incremental Emissions Rate (EIER)

The previously discussed methods for estimating emissions factors rely upon the empirical dependence of total emissions on total output over a predefined period, which could be a year, a season, or any other time period. As a result, they produce emissions factors characteristic of the selected time period, but not indirect emissions factors at an hourly level. However, it is possible to take this analysis to its limit and assess the hourly slope factor by dividing the change in total emissions from one hour to the next by the change in total output for the same hour. This approach results in the empirical incremental emissions rate (EIER), which may be expressed mathematically as follows:

$$EIER_t = \frac{CO_2(t) - CO_2(t-1)}{MW(t) - MW(t-1)} \quad (4)$$

The implicit model underlying this approach is that units which are not marginal or displaceable in any hour will have constant output and emissions, so that the metric will be sensitive only to units which change their output from hour to hour. This theoretically weights the metric by the change in output for these “marginal” plants. In contrast, the hourly average emission rate approach was weighted by the total output of each unit, even for units whose output is insensitive to changes in load.

While the EIER has the attractive feature that it is a direct estimator of the dependence of change in emissions on change in total generation for each hour, there are certain considerations which must be made in its application. First, the estimator does not distinguish between units that change their output because they are in a normal ramping cycle, for example in anticipation of daily changes in load from those that change their output in response to shorter term load fluctuations. This may be problematic as the former may be large units and exhibit large changes in load, so they are likely to dominate the metric during the hours when their output varies. Next is a numerical stability issue: if the change in total generation is small, the calculated EIER could be dominated by reporting and round-off errors in the emissions data. Thus we choose (somewhat arbitrarily) to eliminate hours from consideration if the change in total generation in the region from the previous hour is less than 100 MW. In this case we carry forward the EIER from the previous hour.

Finally, the EIER can be less than zero in some hours. This phenomenon occurs when total reported generation output in some region rises or falls during an hour by an amount greater than the 100 MW threshold, but total reported emissions changes in the other direction. This is not necessarily reporting error; it may well be that changes in dispatch, due to transmission constraints or some other consideration, have enough of an impact on emission rates to offset the effect of changing total output. This instability, and the wide scatter in the hourly results for this approach, cast some doubt on the value of this approach for predicting hour-to-hour indirect emissions benefits associated with renewable energy resources.

E. Load-Following Incremental Emissions Rate (LFIR)

The load-following incremental emissions rate is our name for a hybrid of the hourly average emissions rate and the empirical incremental emissions rate introduced by Stephen Connors in a number of studies of avoided emissions in the United States.^{23,24} The implicit model underlying the LFIR is that units which change their output in the same direction that load is changing during any dispatch period can be treated as load following. Thus the LFIR approach is designed to yield the average emission rate of the units that change output in the direction of changing load during each hour under consideration. However, as Connors notes,²⁵ units which are held for spinning reserves or automatic generation control may actually be load following units, and would be missed by the first criterion. Thus the list of “load following” units must include any unit whose last change in output has been in the direction of the change in total load, even if subsequent hours have produced only small changes in output (less than 2.5% of their maximum.) Finally, Connors examines the range of unit behavior and finds that any unit whose output is between 55% and 90% of its capacity is likely to be providing spinning reserve service, and designates these units as load following as well.²⁶

Following this logic, we find that a large proportion of generating units on the system most of the time would be designated as “load following” in the 2005 EPA database; in many regions, one-third to one-half of all resources earn this designation more than 50% of the time. This brings the effect of this approach close to that of the HAER approach based on all units running, despite the significantly more complicated analysis required. At the same time, because the units (and hence emission rates) may change from hour-to-hour even when total load is changing only slightly, this method suffers from even greater numerical instability than the EIER approach.

Connors describes the logic for selecting load following units as “excessively inclusive”²⁷ in designating too large a proportion of available units in each hour. To remedy this, he weights each unit’s contribution for each hour by its MW change in output from the previous hour. This method may serve to mitigate some of the distortion from large base load resources that happen to make it into the list of “load-following” units by coincidentally ramping along with load, but only for the hours in which they do not happen to be ramping. For the hours when they are, they will clearly dominate the calculated average, as their changes in load will be much greater than that for smaller, truly load-following units.

In summary, we find that the LFIR approach suffers from many of the same distortions as both the EIER approach, and the HAER approach. The LFIR is numerically unstable, producing emissions rates which are highly and unrealistically variable throughout the year, while at the same time it gives undue weight to large units which are likely to have

²³ Connors et al. (2005).

²⁴ Berlinski, and Connors (2006).

²⁵ Ibid., p.1-4.

²⁶ Connors *et al.*, 2005, Table 1.1, p. 1-6.

²⁷ Ibid, p. 1-10.

larger changes in output from hour to hour but are not necessarily likely to be load-following. Although we have calculated and tabulated the estimated indirect emissions benefits using the LFIR for comparison, we conclude that it does not produce a useful metric for estimating displaced emission factors on electricity grids.

F. Flexibility-Weighted Hourly Average Emissions Rate (FW-HAER)

The final method considered, FW-HAER is also based on the premise that only certain units are likely to be displaced by variable output renewable energy resources. This approach attempts to identify load following units based on their operational behavior over the course of the entire study period, rather than during individual hours as with the LFIR method. The FW-HAER approach assigns to each unit a score based on how readily it appears to shift output; this score is then used as a weighting coefficient in calculating the indirect emissions coefficient for each hour.

While it is impossible to determine exactly which units would be load following at any given time given the complexities of dispatch in real electric systems, it is reasonably straightforward to determine which tend to behave in a more or less flexible manner. Large base load units are generally scored lower than smaller units. Units that appear to spend a lot of time ramping in response to load during the year, or that are often found partially dispatched, are ranked as highly displaceable whenever they are running.

To capture these dynamics, the FW-HAER approach tracks how often a plant is in the process of ramping relative to the number of hours it operates during the year, as shown in Equation 5:

$$F_i = \frac{N_{ramping,i}}{N_{operating,i}} \quad (5)$$

Where F is the flexibility coefficient and i refers to an individual unit. A “ramping” hour is defined as any hour in which the change in the unit’s output is greater than or equal to 2.5% of its maximum capacity; by dividing the number of ramping hours by the total number of hours in which the unit operates, we obtain a unit flexibility coefficient which represents the proportion of its operating hours which appear to be in “ramping” mode.

Once the flexibility coefficient of each unit on the system is calculated, the indirect emissions rate for each hour of operations is calculated as shown in Equation 6:

$$FW-HAER_t = \frac{\sum (F_i ER_{i,t})}{\sum F_i} \quad (6)$$

Where $ER_{i,t}$ is the emission rate for unit i during hour t and the summations are over all units operating during that hour, and F_i is as in Equation 5. Again, this method does not weight by either unit size or by the change in output in any given hour. Only units which appear to be more flexible in their output over the year have increased influence on the displaceable emissions rate. This approach avoids giving undue weight to large, inflexible

units, and also exhibits substantially less volatility than methods that are based on hourly changes in output.

The FW-HAER approach has several advantages for estimating the emissions impacts of variable output resources. It does a much better job than any other approach in narrowing the list of candidate units that dominate the indirect emissions calculation. Unlike the other approaches considered here, the FW-HAER avoids giving undue weight to large, inflexible units. FW-HAER is much more numerically stable than either the EIER approach or the LFIR approach, yielding a much smaller range of displaceable emissions rates through the year. Finally, because of this stability and more refined identification of the most flexible units in any region, it does the best job of differentiating regions by their true indirect emissions rates. These features are demonstrated in the figures below.

Figure 14 shows the relationships among flexibility coefficient, generator size, and number of operating hours for (a) New England and (b) California. The size of each circle represents the observed number of operating hours in 2005. In both regions, we see that the very highest flexibility coefficients are attributed to small units which run infrequently; when running, these may also be the first units displaced. In California, it is apparent that the largest units are not displaceable; in New England, there does not appear to be much of a relationship between unit size and flexibility.

Figure 15 shows hourly generation profiles for three sample plants in Florida, exhibiting typical profiles for low, medium, and high flexibility coefficients.

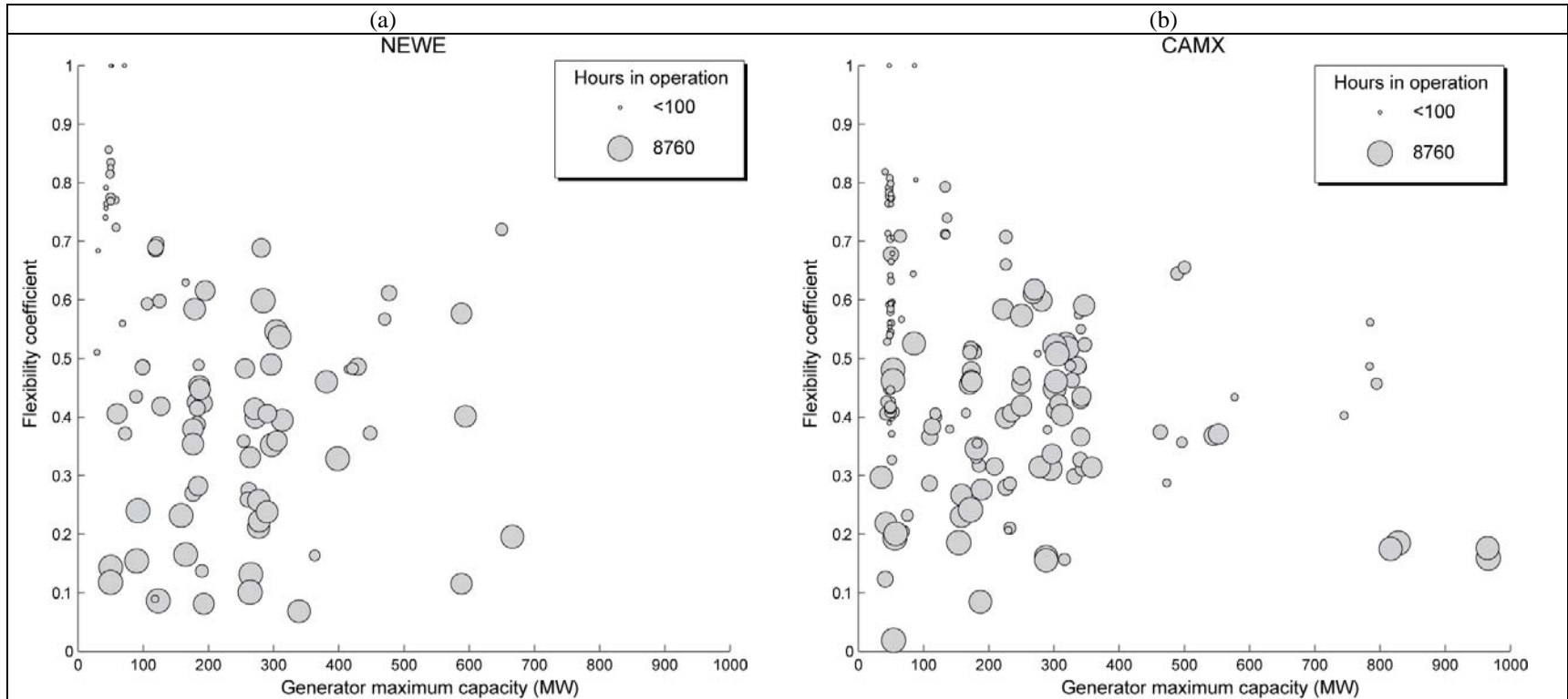


Figure 14. Flexibility coefficient vs. generator size in New England (NEWE) and California (CAMX). Each circle represents a single generating plant in the indicated region, and the size reflects total operating hours in 2005. Maximum size is 8760 hours.

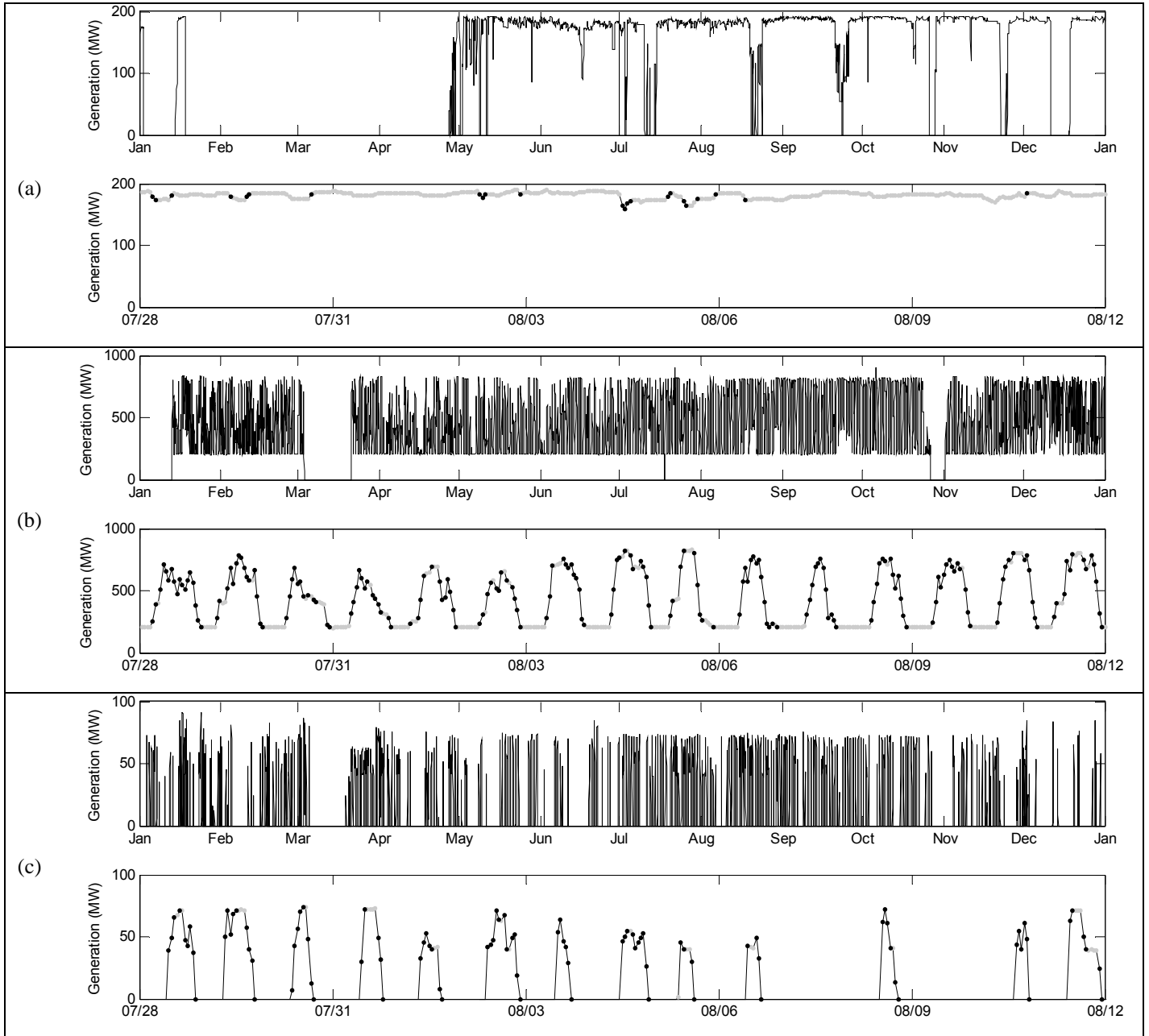


Figure 15. Hourly dispatch and flexibility coefficient (F) for three plants of differing capacities in the FRCC subregion. Each lower graph is a summer detail of the 2005 profile shown above. (a) Polk power plant, $F = 0.08$; (b) Manatee gas plant, $F = 0.55$; (c) Debray peaker, $F = 0.86$.

G. Comparison of Indirect Emissions Rates

It is instructive to compare the implications for indirect emission rates from each estimation approach. Figure 16 displays these results in three panels, for CO₂, SO₂, and NO_x, respectively. Each panel is organized vertically by region, with indirect emission rates on the horizontal axis. For each region, the range (single standard deviation around the mean) of the hourly indirect emission rates may be read and compared for each of the calculation approaches considered. Methods depicted are the empirical incremental emission rate (EIER, solid line), the hourly average emission rate (HAER, angle brackets), and the flexibility-weighted average emission rate (FW-HAER, shaded rectangle).²⁸ Also shown is the annual (CO₂, SO₂) or seasonal (NO_x) slope factor for each region, which is shown as a point as it is not an hourly value but a metric calculated from the annual or seasonal data.

The graphs in Figure 16 illustrate the variations among regions, and within each region between the different calculation approaches. For example, the leftmost panel illustrates that for CO₂, there is general agreement among the different calculation approaches in all regions, although the slope factor tends to suggest a lower indirect emissions rate than other methods. The HAER and the FW-HAER approaches both yield values in a fairly tight range and are generally in agreement with each other, while the EIER approach yields a much broader range of hourly values reflecting its numerical instability. It is also clear from Figure 16 that certain regions, such as the Midwest areas that rely heavily on coal generation, have indirect emissions rates of over 1.0 to 1.2 tCO₂ per MWh, while regions such as California and New England, which rely more heavily on gas, have indirect emissions rates of perhaps 0.6 to 0.8 tCO₂ per MWh.

Color intensity plots for each hourly method for each pollutant, and for each region are provided in Appendix D. These plots display the diurnal and seasonal variations in each displacement factor derived using each approach. The data are also available in electronic format.

²⁸ We have not plotted the single-standard-deviation range based on the LFIR approach in Figures 14-16 because it is far too broad for this scale, reflecting the numerical instability of this approach.

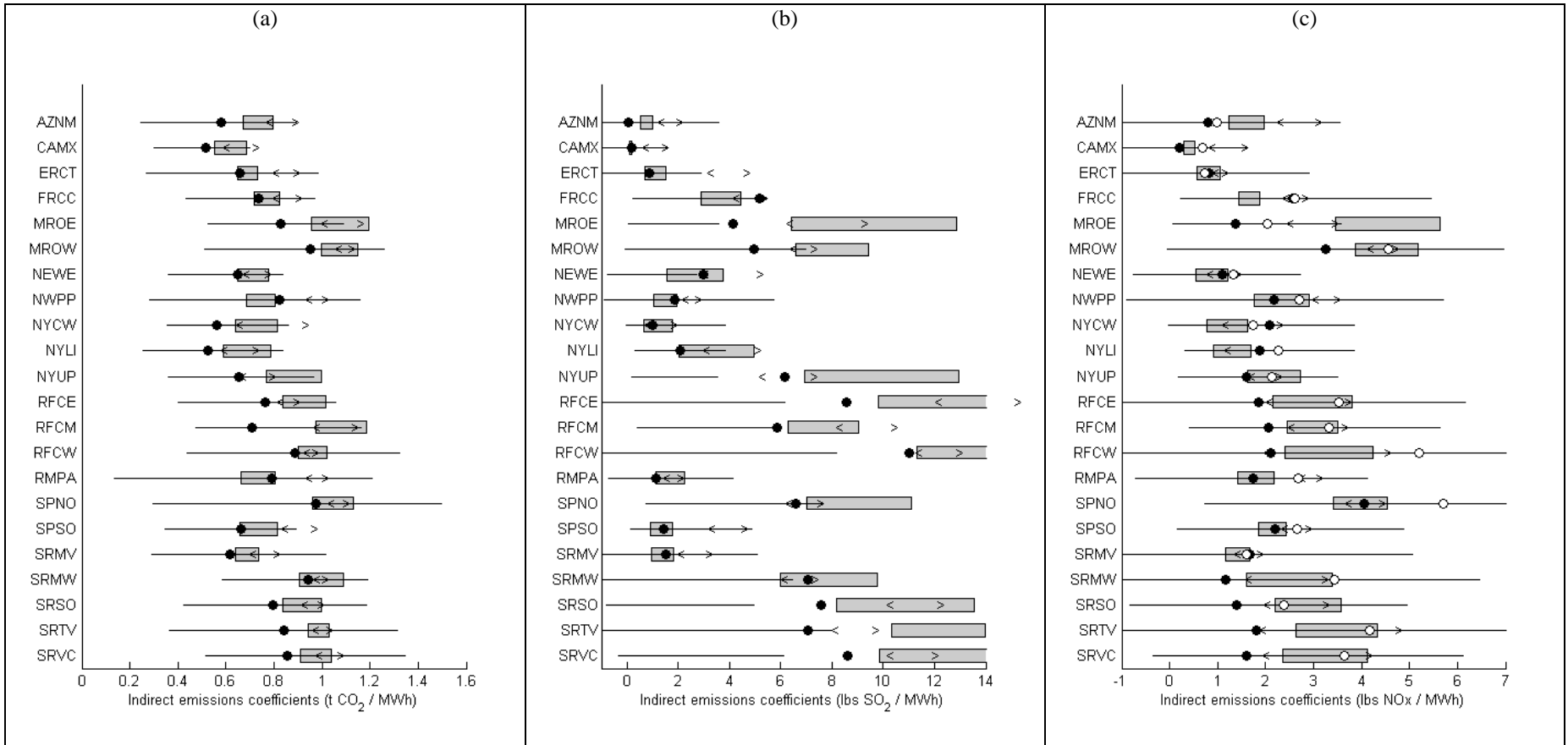


Figure 16. Comparison of the distribution (mean +/- one standard deviation) of indirect emissions coefficients for (a) CO₂, (b) SO₂ and (c) NO_x based on methods described in the text. *Line*: empirical incremental emission rate (EIER); *Angle brackets*: hourly average emission rate (HAER); *Shaded rectangles*: flexibility-weighted hourly average emission rate (FW-HAER). Also shown as round marks are the annual (for CO₂ and SO₂) or seasonal (for NO_x; dark = ozone season) emissions slope factors for each region.

5. Indirect Emissions Results

In this section we present our assessment of what the annual indirect emissions reductions of NO_x, SO₂, and CO₂ would have been in each of the 22 eGRID subregions in 2005, had an incremental renewable energy project (wind, landfill gas, or municipal solid waste) produced one gigawatt-hour (GWh) of energy over the course of the year. As discussed earlier, we find that landfill gas and municipal solid waste have identical base load energy profiles. Thus we have combined the analyses for these two resources into a single set of results.

All of the results presented here are based on a one-to-one displacement of fossil generation, assuming emissions-free generation from the renewable resource. While beyond the current scope, it would improve precision to incorporate line losses, as well as consideration of internal energy use at power plants. In general, renewable generation sites are remote from load centers, meaning that more than one MW of generation is required to serve one MW of load. Fossil generation sites may be near to or remote from load. However, all fossil units have some parasitic load—again, more than one MW must be produced in order to deliver one MW onto the system. The extent to which these cancel out in any given region, or the adjustments that should be made to accommodate them, is beyond the scope of this study.

The calculated indirect emissions results are presented graphically as outlined in Table 4. The results are also tabulated in Table 5 (wind projects) and Table 6 (landfill gas and municipal solid waste.)

Table 4. Guide to the summary figures.

Figure	Resource Type	Pollutant	Methods	Regions
Figure 17	Wind	CO ₂	HAER, EIER, FW-HAER	All eGRID regions
Figure 18	Wind	NO _x	HAER, EIER, FW-HAER	All eGRID regions
Figure 19	Wind	SO ₂	HAER, EIER, FW-HAER	All eGRID regions
Figure 20	MSW, LFG	CO ₂	HAER, seasonal and annual slope factors	All eGRID regions
Figure 21	MSW, LFG	NO _x	HAER, Seasonal Slope Factor	All eGRID regions
Figure 22	MSW, LFG	SO ₂	HAER, Seasonal and Annual Slope Factors	All eGRID regions

The results show significant regional differences in the indirect emissions of all pollutants, no matter what calculation method is used. They also show that the calculation method applied makes a large difference in some regions, while in other regions these differences are less significant. This leads to the question of which method is most appropriate to use under what conditions.

In our judgment, the FW-HAER best captures the short-term operational behavior of power plants because it reflects observations of short-term changes in output for individual plants which respond flexibly to system perturbations. We recommend this approach in particular for shorter-term indirect emissions benefits for CO₂, in response to

variable output, non-dispatchable resources such as wind power. The regional FW-HAER values presented in this paper can be applied for this purpose, where the definition of short-term depends on the application but may be the first two or three years of a new wind resource lifetime.

Over the longer term, and with greater penetration of wind resources, it is reasonable to assume that the system will adjust by displacing resources lower down in the dispatch order, ultimately restoring the utilization rate of load-following capacity to accommodate fluctuations in both load and wind resource output. In addition, NO_x and SO₂ are both regulated under regional or national cap-and-trade regimes which make hourly indirect emissions analysis less relevant for these pollutants. Thus for longer-term indirect CO₂ analysis, or for NO_x and SO₂, we recommend using either HAER or the emissions slope factor. These approaches are based on the longer-term response to perturbations over the full resource portfolio, as opposed to reflecting primarily the marginal unit or units. These two approaches (HAER and slope factor) give generally similar results. The primary difference between them is that the HAER size-weights base load fossil resources running at any given hour, giving the most weight to large units regardless of their flexibility in response to changes in output. Conversely, the slope factor method tends to deemphasize continually operational resources regardless of size. As we find it unlikely that the largest and lowest running cost resources would ever be displaced by renewable energy projects, we prefer the slope factor approach for those regions and pollutants for which the slope factor is well defined.

For landfill gas and municipal solid waste resources, the most likely type of generators to be displaced are intermediate units, which are more costly to run than base load but which do not have the flexibility of load-following resources. In this case, the best method would again be either HAER or the slope factor approach, and we would again give slight preference to the slope factor approach if the slope is well-defined.

Finally we note that most of our results, especially those for CO₂, are relatively insensitive to hourly or seasonal variations in wind power generation. Replacing the calculated wind profiles with a flat power output profile (such as that characteristic of landfill gas or municipal solid waste) results in small changes in the calculated indirect emissions impact over the course of a year. Table 8 shows this result as the percent change in the total annual indirect emissions impact for wind resources if the hourly profile is replaced by a flat profile, typical of an LFG or MSW facility. The small changes suggest that indirect emission factors and wind output profiles are generally poorly correlated, and in many cases little is gained from the effort to apply realistic profiles.

However, some of these differences are larger than others and probably important—for example, in some regions the impact of using a realistic wind-based shape on indirect NO_x emissions is as high as 10%. This difference probably reflects seasonal differences in wind strength which are correlated with seasonal differences in the operation of NO_x control equipment. Whether the effort required to establish realistic wind profiles pays sufficient dividends in this type of analysis to be justified probably depends on the specific application.

Table 5. Annual indirect emissions reduction rates associated with an incremental GWh of wind energy in each of the eGRID subregions for 2005. Calculation methods shown are: *HAER*: Hourly average emission rate; *FW-HAER*: Flexibility-weighted hourly average emission rate; *EIER*: Empirical incremental emissions rate; *LFIR*: Load-following incremental rate; *Slope factor*: Indirect emission rate based on seasonal relationship between emissions and output across all hours in each season. For CO₂ and SO₂ the seasonal slope factors are based on conventional 3-month seasons; for NO_x the slopes are defined for the ozone and non-ozone regulation seasons.

eGrid Region	2005 Avoided CO ₂ (tons/GWh)					2005 Avoided NO _x (lbs/GWh)					2005 Avoided SO ₂ (lbs/GWh)				
	HAER	EIER	LFIR	FW-HAER	Slope Factor	HAER	EIER	LFIR	FW-HAER	Slope Factor	HAER	EIER	LFIR	FW-HAER	Slope Factor
AZNM	844	573	591	738	943	2,768	1,335	1,260	1,641	927	1,782	1,335	1,049	801	218
CAMX	670	497	496	619	892	1,238	259	287	411	508	1,138	259	202	139	216
ERCT	845	606	596	684	1,040	1,058	863	877	785	775	3,920	863	1,300	1,074	1,116
FRCC	845	694	689	757	994	2,645	2,811	2,757	1,675	2,584	4,857	2,811	5,254	3,519	5,454
MROE	1,071	803	807	1,054	1,114	2,981	1,902	2,346	4,380	1,810	7,678	1,902	5,147	9,310	4,738
MROW	1,094	885	884	1,060	1,079	4,456	3,407	3,388	4,461	4,101	6,887	3,407	5,075	7,850	5,451
NEWE	728	588	637	711	780	1,177	1,004	944	913	1,253	4,177	1,004	2,691	2,737	3,126
NWPP	981	716	657	741	1,076	3,267	2,400	2,101	2,310	2,547	2,546	2,400	(1,085)	1,493	1,350
NYCW	800	616	657	717	742	1,821	2,073	957	1,206	1,846	1,452	2,073	1,353	1,251	1,545
NYLI	662	530	621	687	744	1,623	2,277	1,160	1,317	2,158	4,204	2,277	2,804	3,513	2,773
NYUP	731	664	698	875	816	2,016	1,991	1,864	2,172	1,967	6,277	1,991	6,367	9,737	6,015
RFCE	854	724	731	911	896	3,062	2,691	2,485	3,039	3,009	13,596	2,691	9,117	12,842	9,881
RFCM	1,059	835	773	1,072	959	3,194	3,277	3,057	2,988	2,912	9,363	3,277	6,448	7,511	7,420
RFCW	954	885	854	948	906	3,579	3,852	3,496	3,435	4,219	12,250	3,852	11,037	13,443	12,994
RMPA	980	661	612	734	1,056	2,963	1,675	1,011	1,805	2,377	1,848	1,675	708	1,699	895
SPNO	1,066	912	906	1,040	1,074	4,060	4,019	3,203	3,955	4,966	6,949	4,019	6,910	8,953	6,909
SPSO	905	618	629	735	1,062	2,642	2,662	2,610	2,151	2,466	3,912	2,662	1,454	1,331	1,531
SRMV	765	659	653	686	1,027	1,638	1,912	1,900	1,407	1,616	2,693	1,912	2,148	1,404	1,611
SRMW	996	905	900	1,001	966	2,664	2,415	2,489	2,717	2,839	6,739	2,415	6,348	7,941	7,332
SRSO	960	818	826	914	997	2,769	2,300	2,504	2,919	2,089	11,308	2,300	9,293	10,796	7,909
SRTV	1,005	856	882	987	974	3,755	3,270	3,252	3,708	3,499	9,004	3,270	9,463	12,374	7,469
SRVC	1,035	955	837	974	933	3,349	3,177	2,685	3,405	3,029	11,289	3,177	9,302	12,135	9,902

Table 6. Annual indirect emissions reduction rates associated with an incremental GWh of landfill gas of MSW generation in each of the eGRID subregions for 2005. Calculation methods shown are: *HAER*: Hourly average emission rate; *Slope factor*: Indirect emission rate based on seasonal relationship between emissions and output across all hours in each season. For CO₂ and SO₂ the seasonal slope factors are based on conventional 3-month seasons; for NO_x the slopes are defined for the ozone and non-ozone regulation seasons.

eGrid Region	2005 Avoided CO ₂ (tons/GWh)		2005 Avoided NO _x (lbs/GWh)		2005 Avoided SO ₂ (lbs/GWh)	
	Slope		Slope		Slope	
	HAER	Factor	HAER	Factor	HAER	Factor
AZNM	838	943	2,718	901	1,710	223
CAMX	667	893	1,226	476	1,129	206
ERCT	852	1,042	1,069	775	3,981	1,080
FRCC	859	995	2,632	2,582	4,806	5,442
MROE	1,086	1,117	2,996	1,764	7,834	4,649
MROW	1,098	1,080	4,459	4,022	6,891	5,307
NEWE	732	777	1,138	1,232	4,140	3,119
NWPP	982	1,078	3,274	2,472	2,553	1,362
NYCW	795	740	1,739	1,887	1,339	1,482
NYLI	660	740	1,549	2,110	4,103	2,645
NYUP	736	812	2,004	1,917	6,306	6,003
RFCE	862	898	2,904	2,829	13,720	9,424
RFCM	1,058	958	3,103	2,787	9,380	7,164
RFCW	956	905	3,303	3,900	12,187	12,688
RMPA	980	1,055	2,952	2,278	1,830	974
SPNO	1,069	1,075	4,088	5,012	6,949	7,005
SPSO	909	1,062	2,653	2,464	3,958	1,549
SRMV	764	1,025	1,660	1,628	2,665	1,593
SRMW	999	970	2,458	2,482	6,773	7,226
SRSO	961	997	2,654	1,976	11,269	7,601
SRTV	1,004	975	3,366	3,175	8,927	7,327
SRVC	1,032	932	3,096	2,790	11,168	9,529

Table 7. “Shape impact” for indirect emissions calculations for each pollutant in each eGrid region. The shape impact is the change in calculated indirect emissions if an hourly wind profile is replaced with a constant generation profile with the same total output.

eGrid Region	CO ₂ Shape Impact		NO _x Shape Impact		SO ₂ Shape Impact	
	Slope		Slope		Slope	
	HAER	Factor	HAER	Factor	HAER	Factor
AZNM	-0.7%	-0.1%	-1.8%	-2.8%	-4.0%	2.2%
CAMX	-0.4%	0.0%	-0.9%	-6.3%	-0.8%	-4.6%
ERCT	0.9%	0.2%	1.0%	-0.1%	1.5%	-3.2%
FRCC	1.7%	0.1%	-0.5%	-0.1%	-1.0%	-0.2%
MROE	1.5%	0.3%	0.5%	-2.5%	2.0%	-1.9%
MROW	0.3%	0.1%	0.1%	-1.9%	0.1%	-2.6%
NEWE	0.5%	-0.4%	-3.3%	-1.7%	-0.9%	-0.2%
NWPP	0.2%	0.2%	0.2%	-2.9%	0.3%	0.8%
NYCW	-0.7%	-0.2%	-4.5%	2.2%	-7.8%	-4.1%
NYLI	-0.3%	-0.5%	-4.6%	-2.2%	-2.4%	-4.6%
NYUP	0.6%	-0.4%	-0.6%	-2.5%	0.5%	-0.2%
RFCE	0.9%	0.2%	-5.1%	-6.0%	0.9%	-4.6%
RFCM	-0.1%	-0.1%	-2.8%	-4.3%	0.2%	-3.4%
RFCW	0.1%	-0.2%	-7.7%	-7.6%	-0.5%	-2.4%
RMPA	0.0%	-0.1%	-0.4%	-4.2%	-1.0%	8.8%
SPNO	0.3%	0.1%	0.7%	0.9%	0.0%	1.4%
SPSO	0.4%	0.1%	0.4%	-0.1%	1.2%	1.1%
SRMV	-0.1%	-0.2%	1.3%	0.7%	-1.0%	-1.1%
SRMW	0.3%	0.5%	-7.7%	-12.6%	0.5%	-1.5%
SRSO	0.1%	0.0%	-4.2%	-5.4%	-0.3%	-3.9%
SRTV	-0.1%	0.1%	-10.4%	-9.3%	-0.9%	-1.9%
SRVC	-0.3%	0.0%	-7.6%	-7.9%	-1.1%	-3.8%

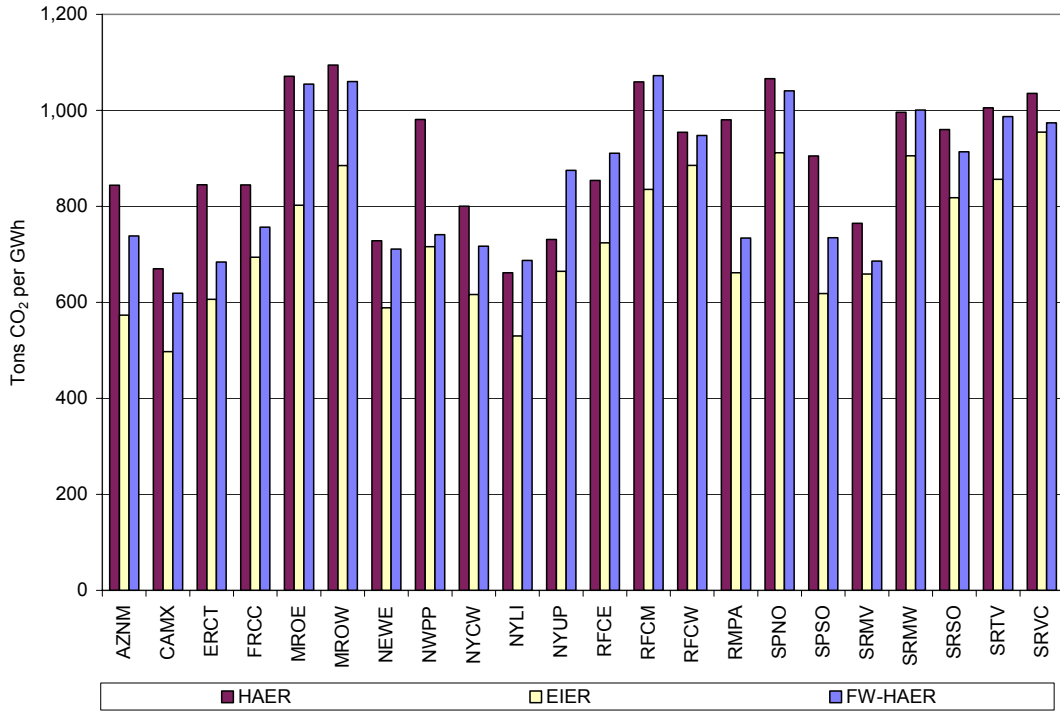


Figure 17. Annual indirect CO₂ emissions impact associated with one incremental GWh of wind energy in each of the eGRID subregions for 2005.

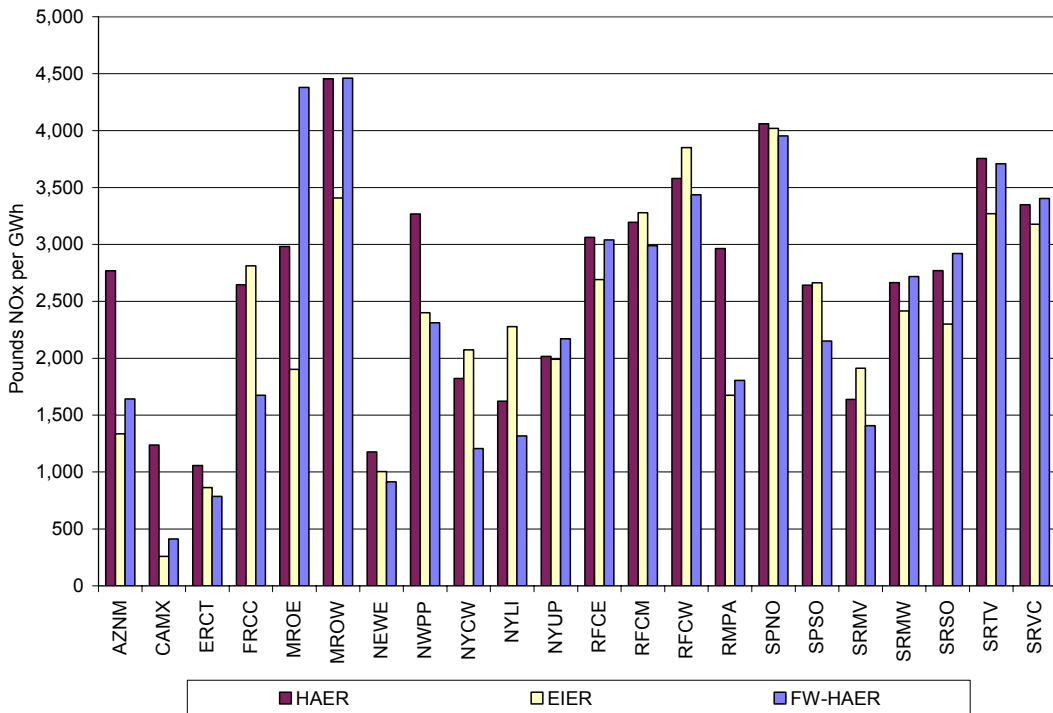


Figure 18. Annual indirect NO_x emissions impact associated with one incremental GWh of wind energy in each of the eGRID subregions for 2005.

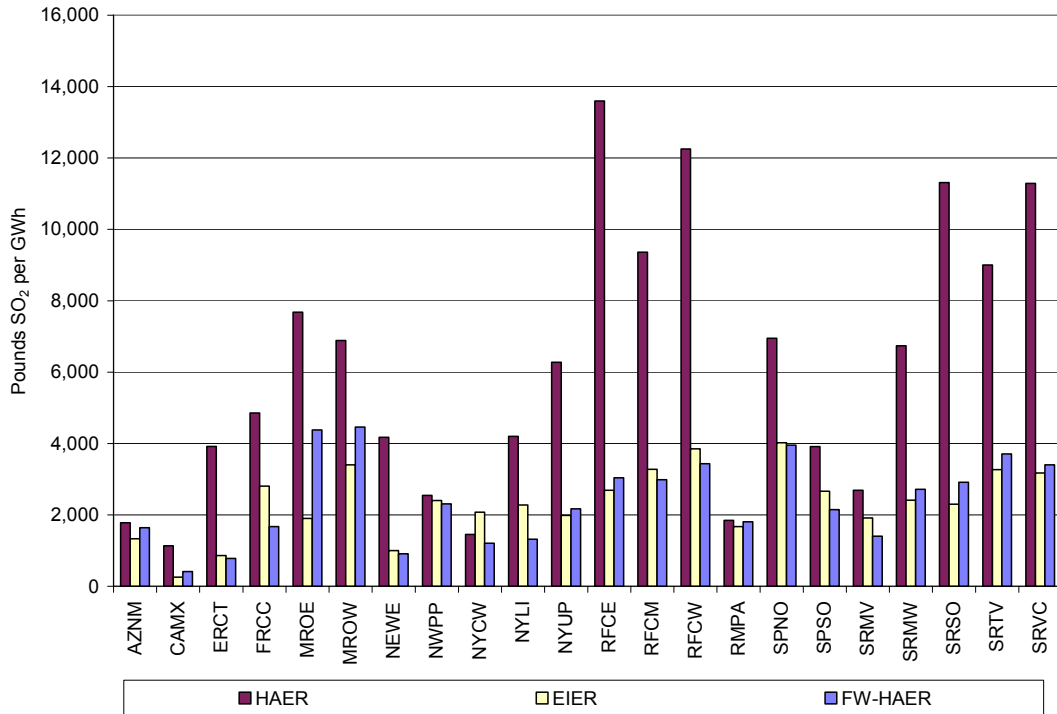


Figure 19. Annual indirect SO₂ emissions impact associated with one incremental GWh of wind energy in each of the eGRID subregions for 2005.

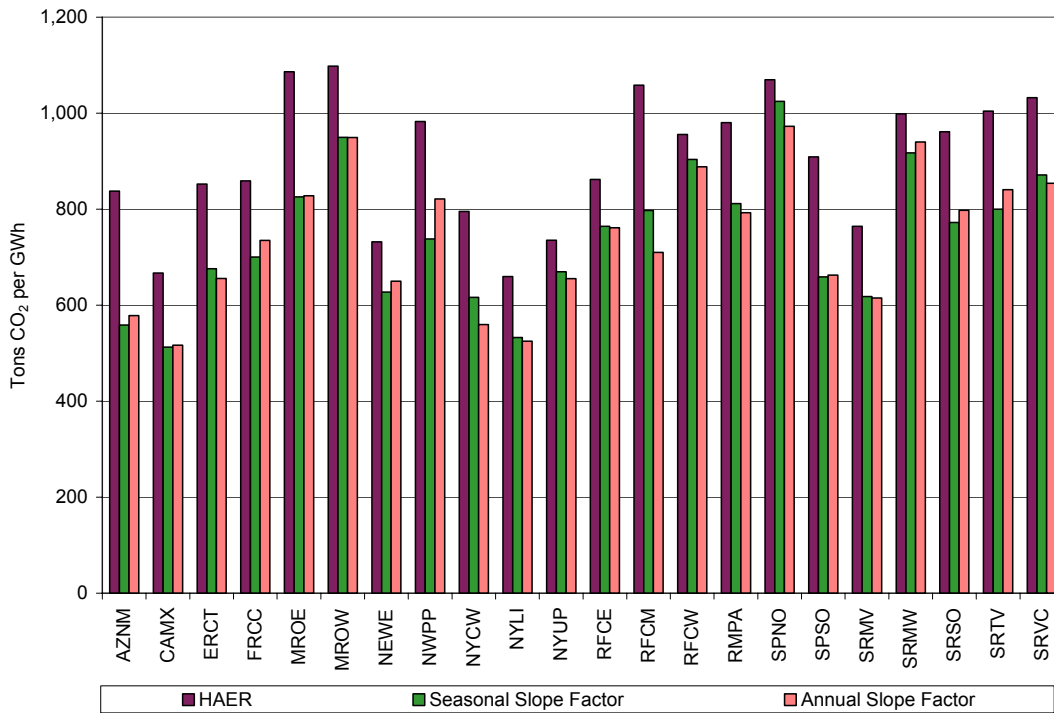


Figure 20. Annual indirect CO₂ emissions impact associated with one incremental GWh of landfill gas or municipal solid waste energy in each of the eGRID subregions for 2005.

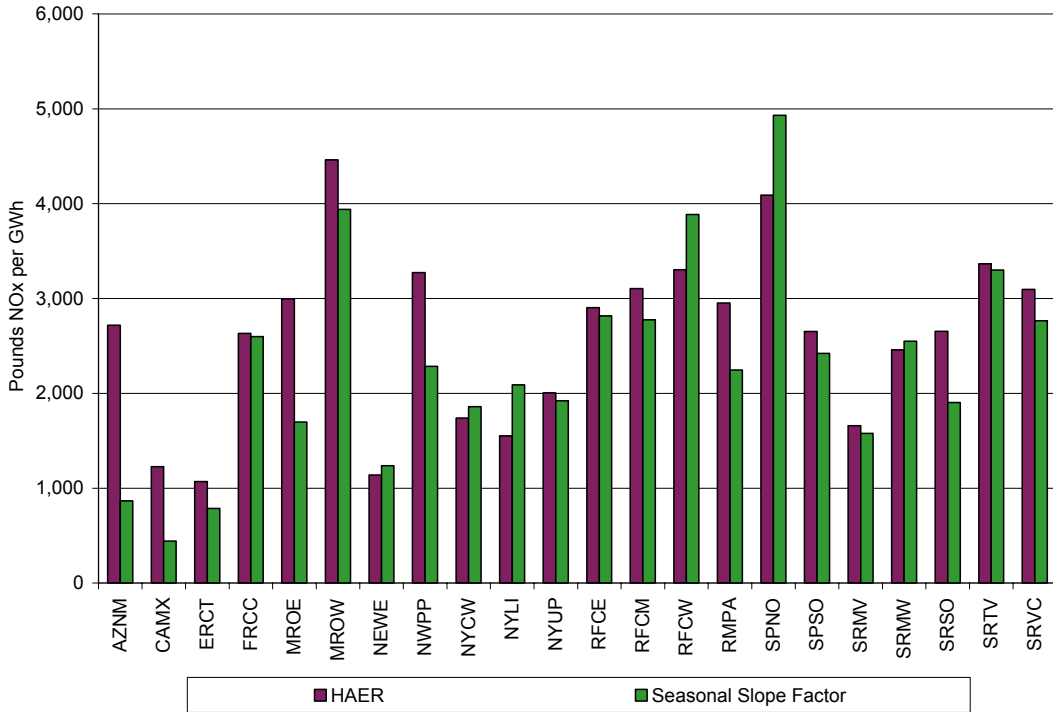


Figure 21. Annual indirect NOx emissions impact associated with an incremental GWh of landfill gas or municipal solid waste energy in each of the eGRID subregions for 2005.

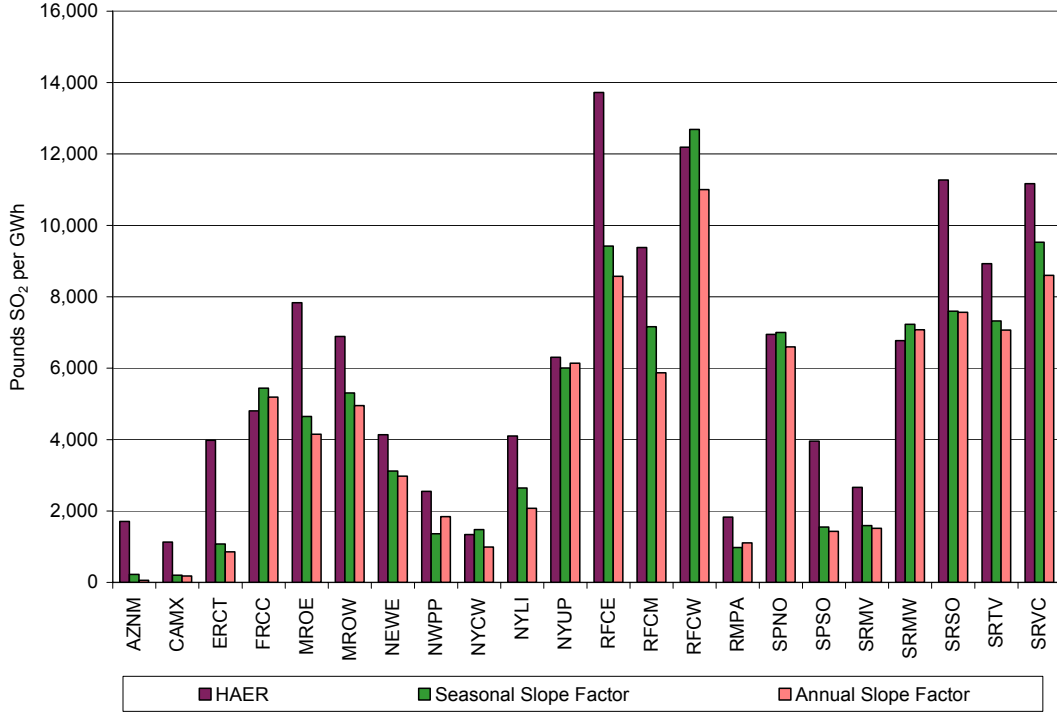


Figure 22. Annual indirect SO₂ emissions impact associated with an incremental GWh of landfill gas or municipal solid waste energy in each of the eGRID subregions for 2005.

6. Conclusions

In this analysis we have produced and applied a number of approaches for calculating indirect emissions impacts and provided a general discussion of which might be more appropriate under different circumstances. We have calculated indirect emissions benefits associated with CO₂, NO_x, and SO₂ for wind, landfill gas, and municipal solid waste electricity generating resources, in each of the 22 eGRID subregions of the continental United States.

The indirect emissions benefit calculated for any kind of renewable energy resource depends on a number of questions:

- Where is the resource located?
- What is the pollutant of interest? Is there a cap and trade system in place for this pollutant?
- Is the time period of interest historical, in the near future, or several years in the future?
- Is the resource base load, dispatchable, or intermittent and nondispatchable?
- If intermittent and nondispatchable, what is the expected hourly and seasonal profile of the resource?

We have found that there are important regional differences in indirect emissions which can be quantified in ways that will be useful for estimating the emissions benefits of renewable energy projects in each region.

Because of the wide range of applications reflected in the possible answers to the questions posed above, the best method to use in calculating indirect emissions is almost certainly application-specific. We believe that these methodologies provide useful guidance for many applications, and a better understanding of the issues for approximation of indirect emissions benefits than has previously been available.

The results presented here could be validated by a modeling analysis, using a full electric system dispatch model to simulate actual indirect emissions under realistic unit commitment and dispatch conditions. The results could then be compared to those that would be derived using each of the methods applied here. This comparison would provide an empirical basis for establishing which approach is most consistent and accurate in predicting indirect emissions in any particular region or under specific circumstances, at least in the context of the model.

In summary, we have found that:

- The indirect emissions benefits of renewable energy for all pollutants vary significantly by region, and these differences can be quantified and applied in calculating indirect emissions impacts;
- Different calculation approaches are appropriate for different types of resources and different applications;

- In general, hourly profiles of renewable energy resources make only a modest difference in quantifying annual indirect emissions benefits;
- More research is needed to establish which methods of calculating indirect emissions benefits most accurately reflect real-world dispatch over a range of timescales and system conditions.

Finally, we note again that the geographic coverage of this analysis was by necessity coarse, in the interest of presenting results for the entire continental United States, particularly with respect to wind resources. For the analysis to be applied to calculate or predict indirect emissions impacts for specific projects, the tables of hourly avoidable emissions data in Appendix D could be applied directly to site-specific operational and meteorological data. However, given the modest impact of differences in hourly profiles noted above, the annual results presented here are likely to be sufficient for most purposes.

Appendix A:

Identification and map of eGRID subregions

eGRID Subregion Representational Map

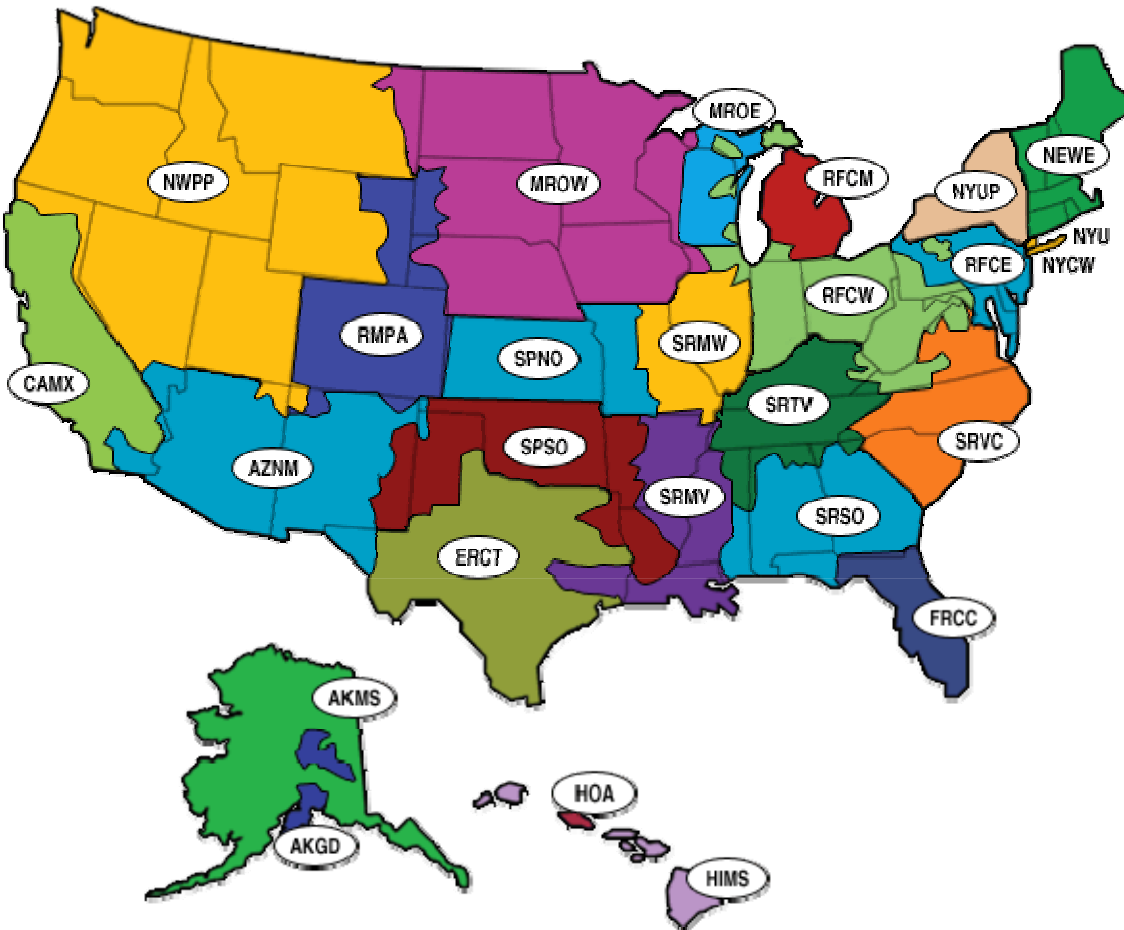


Figure A-1. Map of eGRID subregions. Subregions in Alaska and Hawaii are not considered in this analysis. Acronyms are defined below. Source of figure: https://www.energystar.gov/istar/pmpam/help/eGRID_Subregion_Map.htm.

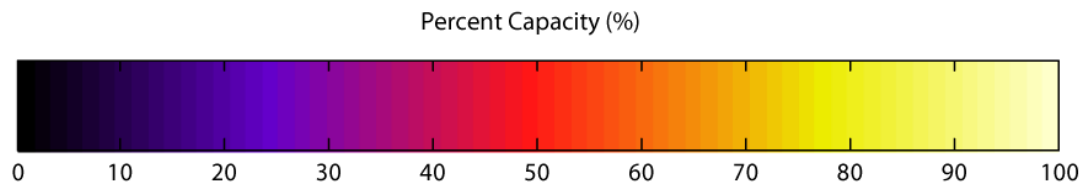
AZNM	Arizona and New Mexico	RFCE	Reliability First - East
CAMX	California	RFCM	Reliability First - Michigan
ERCT	ERCOT (Texas)	RFCW	Reliability First - West
FRCC	FRCC (Florida)	RMPA	Rocky Mountain region
MROE	Midwest Reliability - East	SPNO	Southwest Power Pool - North
MROW	Midwest Reliability - West	SPSO	Southwest Power Pool - South
NEWWE	New England	SRMV	SERC - Mississippi Valley
NWPP	Northwest	SRMW	SERC - Midwest
NYCW	New York City/ Westchester	SRSO	SERC - South
NYLI	New York - Long Island	SRTV	SERC - Tennessee Valley
NYUP	New York - Upstate	SRVC	SERC - Virginia/Carolina

Appendix B:

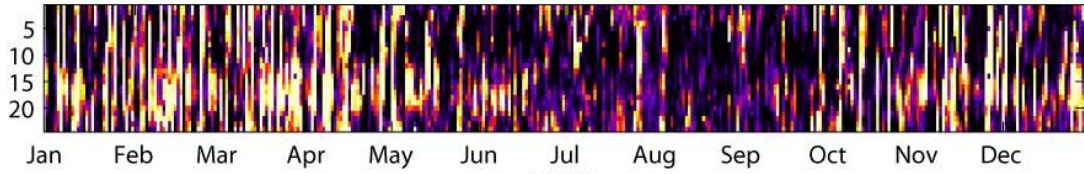
Color intensity plots of synthetic wind power time series (hourly percent of capacity) for each eGRID subregion. Each grid shows hour of the day on the vertical axis and days of the year on the horizontal axis. Color scale for all charts is shown below and at the bottom of the last page.

These data were obtained by scaling publicly available ground-level meteorological data to a typical turbine height and class 4 wind strength (Equation 1 in the text) and then transforming into wind power output using Equation 2.

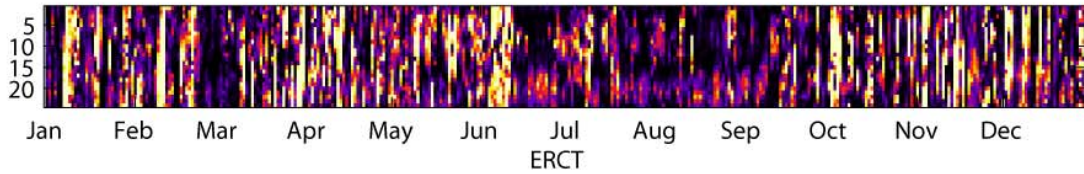
The hourly data are available in electronic format upon request.



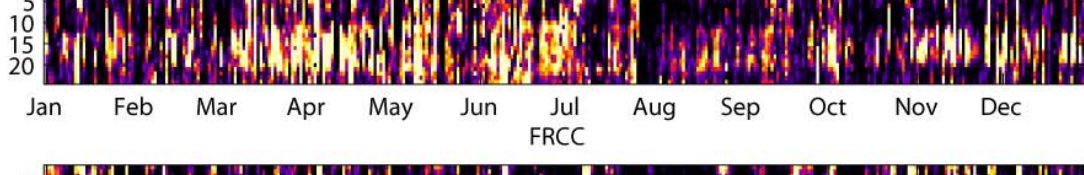
AZNM



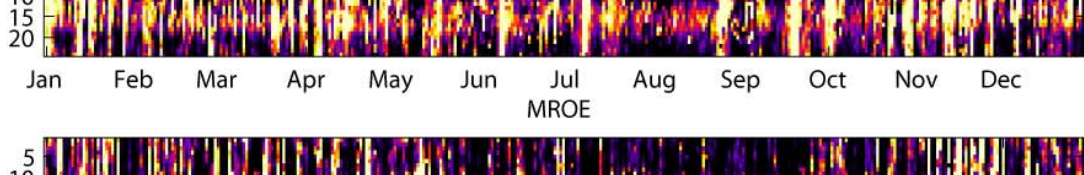
CAMX



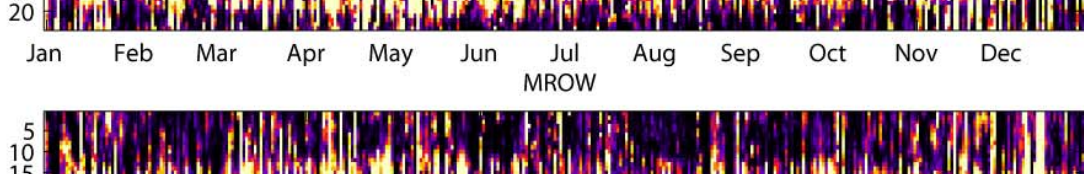
ERCT



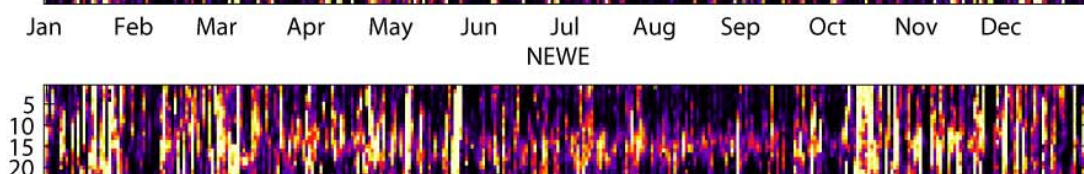
FRCC



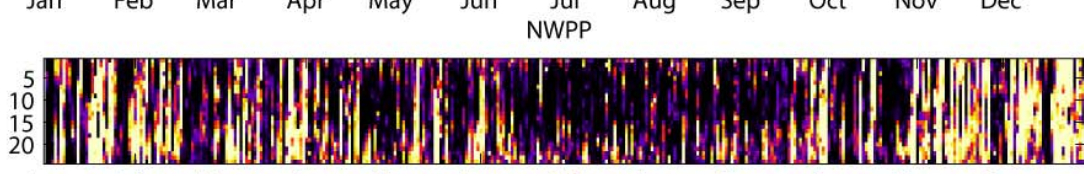
MROE



MROW



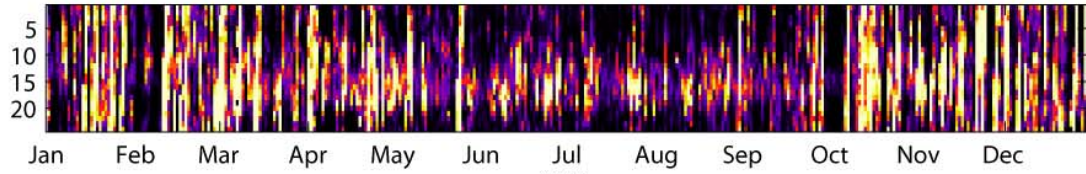
NEWE



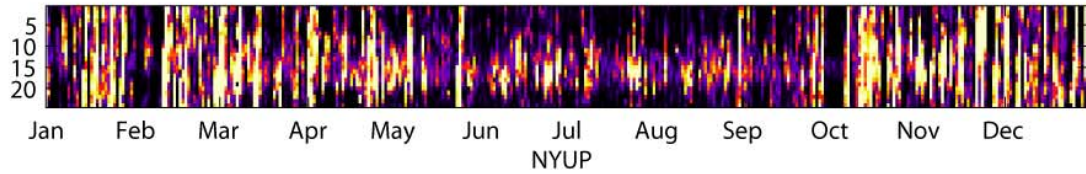
NWPP



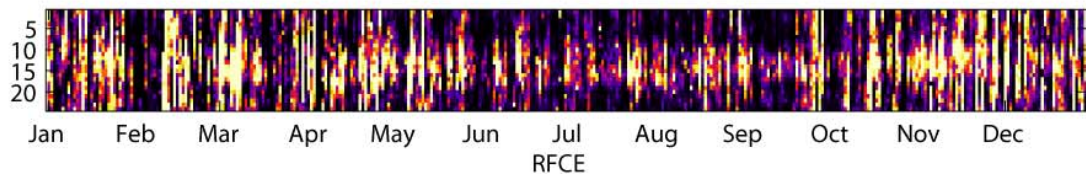
NYCW



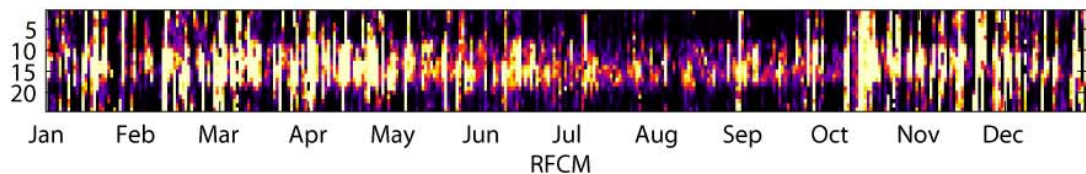
NYLI



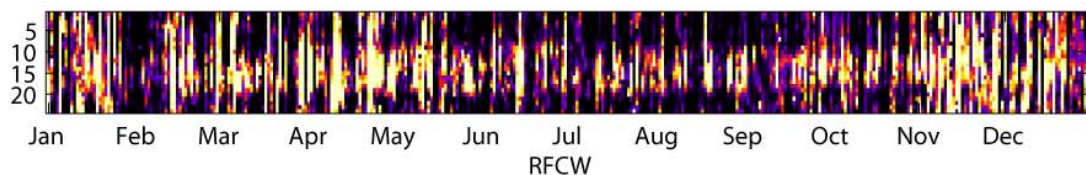
NYUP



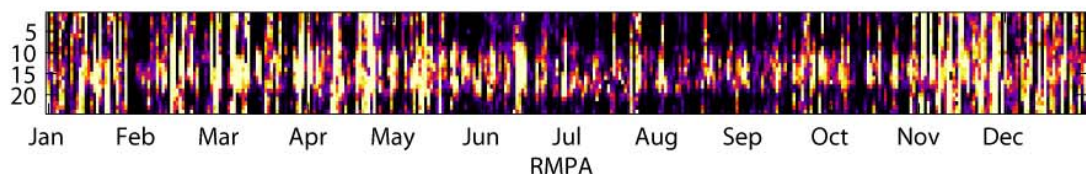
RFCE



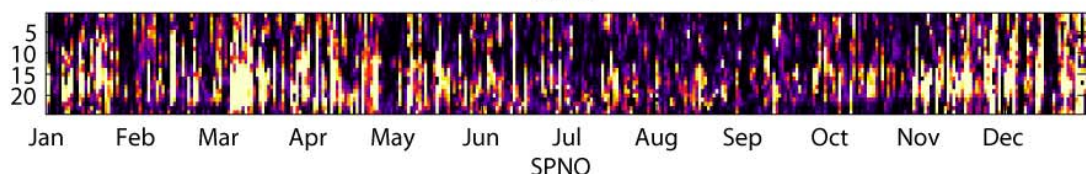
RFCM



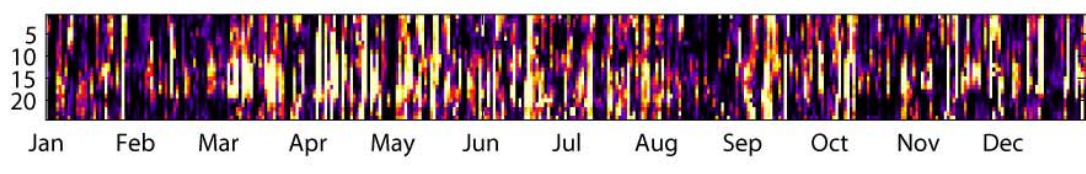
RFCW



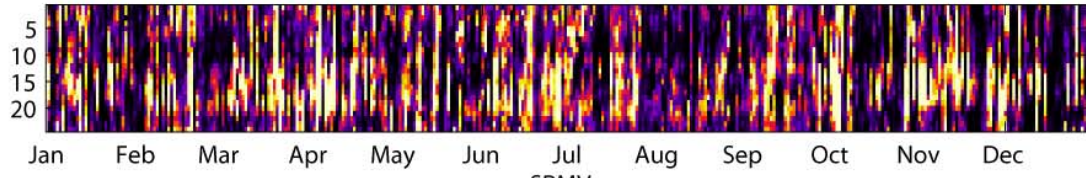
RMPA



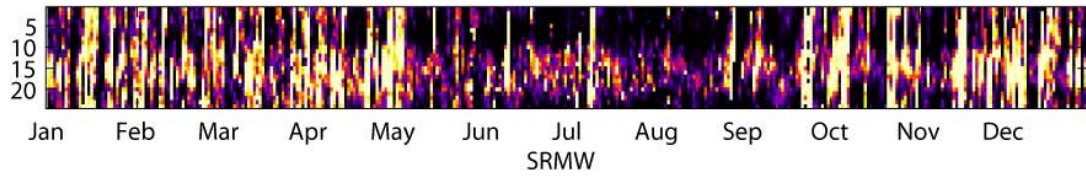
SPNO



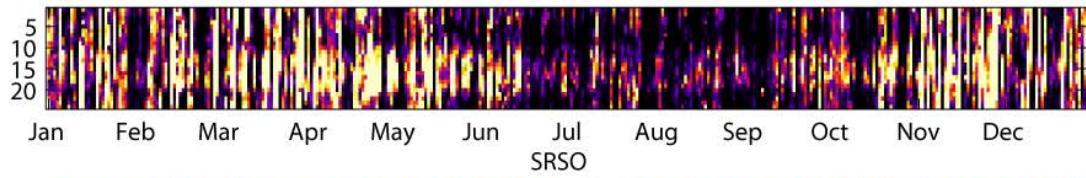
SPSO



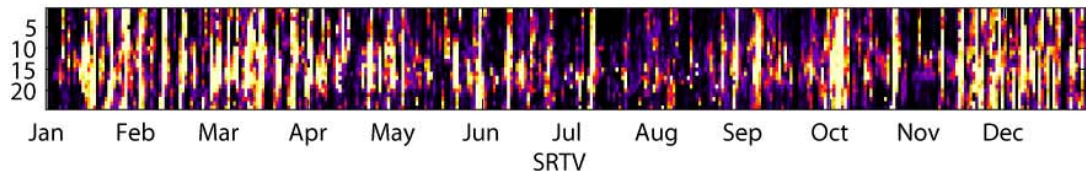
SRMV



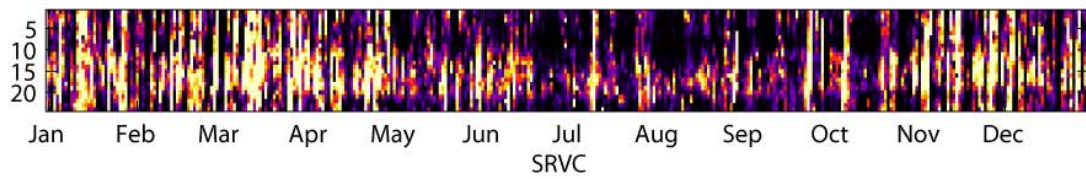
SRMW



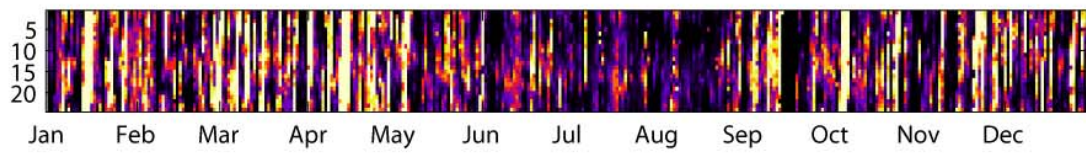
SRSO



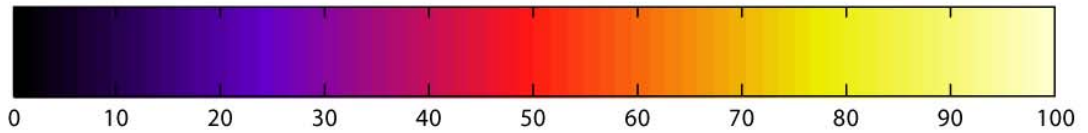
SRTV



SRVC



Percent Capacity (%)

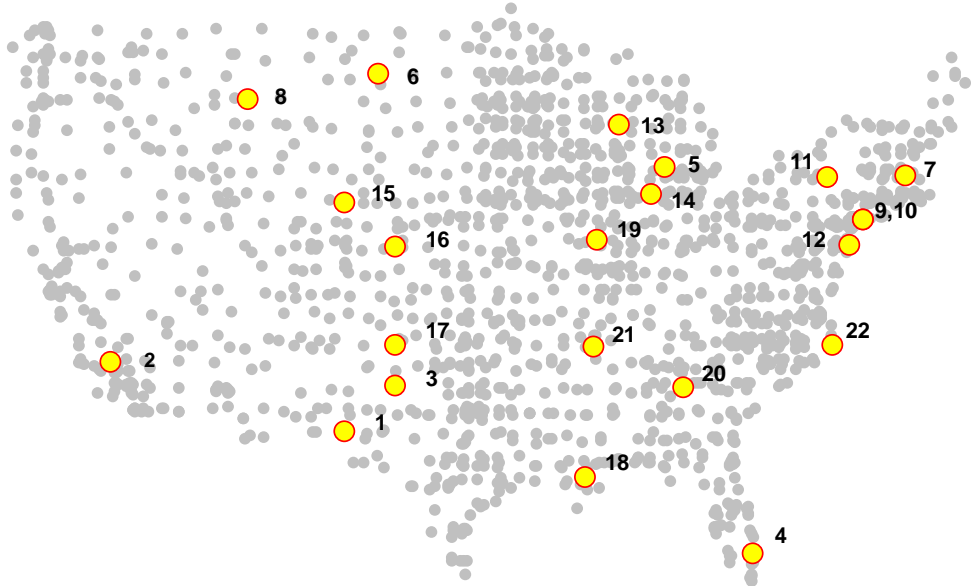


Appendix C:

Summary tables of raw and scaled wind speed and synthetic wind power time series. Monthly summaries are shown for each eGRID subregion.

The hourly data are available in electronic format upon request

The proxy wind turbine locations are shown below, overlaid on map of all U.S. WBAN stations.



Index	NERC Subregion	WBAN Number	Location	Latitude	Longitude
1	AZNM	23055	GUADALUPE PASS, TX	31.5	-104.49
2	CAMX	23187	SANDBERG, CA	34.44	-118.43
3	ERCT	23042	LUBBOCK, TX	33.4	-101.49
4	FRCC	12844	WEST PALM BEACH, FL	26.41	-80.06
5	MROE	14898	GREEN BAY, WI	44.31	-88.07
6	MROW	24012	DICKINSON, ND	46.48	-102.48
7	NEWE	14739	BOSTON, MA	42.22	-71.01
8	NWPP	24150	LIVINGSTON, MT	45.42	-110.27
9	NYCW	94789	NEW YORK, NY	40.4	-73.48
10	NYLI	94789	NEW YORK, NY	40.4	-73.48
11	NYUP	4725	BINGHAMTON, NY	42.13	-75.59
12	RFCE	93730	ATLANTIC CITY, NJ	39.28	-74.28
13	RFCM	94860	GRAND RAPIDS, MI	42.53	-85.31
14	RFCW	14848	SOUTH BEND, IN	41.43	-86.2
15	RMPA	24018	CHEYENNE, WY	41.1	-104.49
16	SPNO	23065	GOODLAND, KS	39.22	-101.41
17	SPSO	23047	AMARILLO, TX	35.13	-101.43
18	SRMV	12916	NEW ORLEANS, LA	29.59	-90.15
19	SRMW	93822	SPRINGFIELD, IL	39.51	-89.41
20	SRSO	13874	ATLANTA, GA	33.38	-84.26
21	SRTV	13893	MEMPHIS, TN	35.04	-89.59
22	SRVC	93729	CAPE HATTERAS, NC	35.14	-75.37

**Monthly average interpolated wind speed (mph)
from representative WBAN station in each NERC subregion**

	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sept	Oct	Nov	Dec
AZNM	19.63	21.52	22.01	20.21	16.42	15.69	15.94	13.56	14.98	16.82	19.53	19.26
CAMX	14.08	13.99	13.37	14.91	14.43	14.16	12.23	11.38	11.39	13.43	15.19	13.98
ERCT	10.61	10.36	13.24	14.15	12.49	13.87	10.74	9.23	10.37	9.69	11.24	10.86
FRCC	10.49	8.74	8.99	10.33	8.44	8.85	8.97	7.67	9.07	10.69	10.40	8.48
MROE	9.23	8.34	9.12	9.59	9.27	8.04	6.98	6.44	6.41	7.36	10.58	7.67
MROW	11.78	10.66	13.27	14.23	12.74	10.95	10.83	10.56	10.52	11.14	13.14	13.25
NEWE	12.32	10.86	12.21	11.29	11.53	9.75	10.45	9.18	9.69	12.67	11.02	11.49
NWPP	15.95	14.12	15.85	12.57	12.15	11.63	9.35	10.30	12.52	12.35	18.28	19.86
NYCW	12.33	11.71	13.01	12.40	10.97	10.28	9.42	9.75	10.31	12.10	13.11	12.68
NYLI	12.33	11.71	13.01	12.40	10.97	10.28	9.42	9.75	10.31	12.10	13.11	12.68
NYUP	8.11	7.23	8.37	8.35	8.00	6.72	7.00	7.22	7.36	7.58	10.18	8.87
RFCE	8.15	8.77	10.40	10.72	8.30	8.17	6.85	6.26	6.94	9.58	9.36	8.85
RFCM	9.49	8.23	8.90	10.23	8.68	7.90	7.36	7.32	8.32	7.98	12.82	9.93
RFCW	9.23	8.40	9.26	10.53	8.58	8.08	7.05	6.11	7.19	6.94	12.31	9.88
RMPA	11.03	11.36	13.99	13.03	11.14	11.01	9.86	9.80	9.70	10.07	14.79	13.47
SPNO	10.20	9.73	13.26	14.24	12.76	12.91	12.76	9.74	12.28	11.23	12.64	11.57
SPSO	11.87	12.04	13.01	14.29	11.71	14.10	12.50	10.55	13.01	11.86	13.02	10.90
SRMV	8.94	8.79	8.39	9.93	7.47	6.12	7.08	5.45	8.33	8.57	8.30	9.02
SRMW	9.86	9.37	11.32	10.93	9.26	7.52	6.34	5.74	6.35	7.60	12.36	9.58
SRSO	8.92	8.72	10.08	8.96	7.71	7.66	5.82	7.03	7.61	8.48	8.80	9.33
SRTV	9.75	8.60	10.39	9.35	7.38	7.03	7.10	6.64	7.04	6.81	9.43	8.46
SRVC	10.60	9.51	11.27	12.02	9.59	8.65	7.44	7.25	9.04	10.18	9.69	9.52

**Monthly average interpolated representative wind speed
scaled to Class 4 (16.25 mph average) for each NERC subregion**

	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sept	Oct	Nov	Dec
AZNM	38.64	42.36	43.33	39.78	32.32	30.89	31.38	26.70	29.48	33.12	38.44	37.92
CAMX	28.04	27.86	26.63	29.68	28.74	28.19	24.35	22.67	22.68	26.74	30.24	27.84
ERCT	21.49	20.98	26.82	28.65	25.29	28.09	21.76	18.69	21.00	19.62	22.76	21.99
FRCC	13.75	11.45	11.79	13.55	11.06	11.61	11.76	10.06	11.90	14.02	13.64	11.12
MROE	8.36	7.55	8.26	8.68	8.40	7.28	6.33	5.83	5.80	6.66	9.58	6.95
MROW	16.50	14.93	18.60	19.94	17.85	15.34	15.18	14.80	14.74	15.61	18.40	18.57
NEWE	14.79	13.03	14.66	13.55	13.83	11.70	12.54	11.02	11.63	15.20	13.23	13.80
NWPP	18.86	16.70	18.74	14.87	14.37	13.75	11.06	12.18	14.81	14.60	21.61	23.48
NYCW	18.14	17.23	19.14	18.24	16.13	15.12	13.86	14.35	15.16	17.80	19.29	18.66
NYLI	23.51	22.32	24.81	23.64	20.91	19.60	17.95	18.59	19.64	23.07	24.99	24.18
NYUP	14.24	12.68	14.69	14.65	14.04	11.80	12.28	12.67	12.91	13.30	17.87	15.56
RFCE	13.85	14.91	17.68	18.22	14.10	13.88	11.64	10.63	11.79	16.28	15.91	15.05
RFCM	18.69	16.23	17.54	20.16	17.11	15.58	14.51	14.43	16.40	15.73	25.27	19.57
RFCW	16.96	15.44	17.02	19.35	15.76	14.85	12.96	11.23	13.21	12.75	22.63	18.16
RMPA	20.79	21.40	26.36	24.56	20.99	20.76	18.58	18.47	18.28	18.97	27.87	25.39
SPNO	13.88	13.23	18.03	19.36	17.36	17.55	17.36	13.24	16.70	15.26	17.19	15.73
SPSO	21.61	21.92	23.68	26.02	21.31	25.66	22.76	19.20	23.67	21.59	23.70	19.83
SRMV	12.18	11.97	11.43	13.53	10.18	8.34	9.64	7.43	11.34	11.67	11.30	12.29
SRMW	20.22	19.22	23.23	22.42	19.00	15.42	13.01	11.78	13.03	15.59	25.36	19.66
SRSO	12.60	12.31	14.24	12.65	10.89	10.83	8.21	9.92	10.75	11.98	12.43	13.18
SRTV	13.77	12.14	14.68	13.21	10.42	9.93	10.03	9.38	9.95	9.62	13.32	11.94
SRVC	15.10	13.55	16.06	17.13	13.67	12.33	10.61	10.33	12.89	14.51	13.81	13.57

**Monthly average calculated wind power output from 1.5 MW proxy turbine
in each NERC subregion (dropout at 56 mph)**

	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sept	Oct	Nov	Dec
AZNM	883.49	919.73	910.01	823.61	879.14	1056.20	1102.16	988.58	990.65	901.21	849.34	987.33
CAMX	971.55	941.26	865.85	1048.52	1101.11	1005.35	924.58	835.30	803.95	906.92	1037.77	971.48
ERCT	680.73	670.23	929.82	902.22	899.96	1121.26	769.51	577.06	692.23	604.10	675.85	672.41
FRCC	286.16	166.17	190.93	268.04	137.00	198.17	193.28	149.79	199.06	267.63	256.74	164.98
MROE	58.62	23.10	51.41	64.85	47.93	28.74	14.36	11.58	17.25	16.27	113.47	21.29
MROW	439.92	343.82	573.12	655.90	518.31	386.22	329.69	343.77	336.63	391.38	559.79	532.01
NEWE	338.89	213.95	272.13	241.16	286.37	119.42	156.53	107.23	138.02	363.12	251.55	254.57
NWPP	572.73	479.22	574.52	402.75	358.02	323.25	185.49	229.19	368.41	354.81	786.22	880.60
NYCW	546.35	504.41	589.69	577.93	406.64	330.33	276.92	288.96	336.61	572.02	633.20	574.40
NYLI	822.24	767.69	848.34	849.13	677.99	606.39	531.39	556.41	649.84	812.71	851.24	858.86
NYUP	335.36	324.15	368.73	377.29	294.03	158.21	171.78	197.17	225.59	261.58	491.64	368.78
RFCE	356.54	394.50	540.16	584.68	341.90	271.12	169.22	164.24	237.97	498.45	501.62	415.26
RFCM	638.43	477.22	605.68	721.99	549.50	423.01	363.23	354.43	452.75	446.94	890.43	673.93
RFCW	506.60	413.12	549.15	606.09	457.05	350.10	281.30	208.01	304.92	264.16	780.63	548.80
RMPA	644.99	659.34	895.00	835.90	664.56	643.43	566.71	526.45	522.83	602.56	813.64	838.43
SPNO	290.58	217.16	515.08	587.51	515.45	497.59	490.45	233.00	451.34	366.46	414.62	362.94
SPSO	752.59	766.10	815.82	878.05	735.24	1004.26	859.04	625.42	912.29	697.96	848.84	601.09
SRMV	202.22	177.89	160.16	283.73	114.13	67.34	106.24	62.86	207.91	207.15	209.46	216.39
SRMW	677.87	624.12	797.53	796.78	637.27	390.96	274.41	204.13	305.80	480.58	898.76	648.20
SRSO	253.66	227.19	310.51	235.63	127.92	139.60	91.58	92.51	97.90	210.36	218.47	209.75
SRTV	258.66	200.36	335.47	242.64	97.73	87.17	94.79	87.37	108.31	100.74	289.18	168.19
SRVC	353.12	226.16	407.72	500.17	228.59	172.78	90.20	88.40	237.99	312.39	281.43	262.02

Appendix D:

Color intensity maps of hourly indirect CO₂, NO_x and SO₂ emissions rates for each eGRID subregion, using several alternative calculation methodologies.

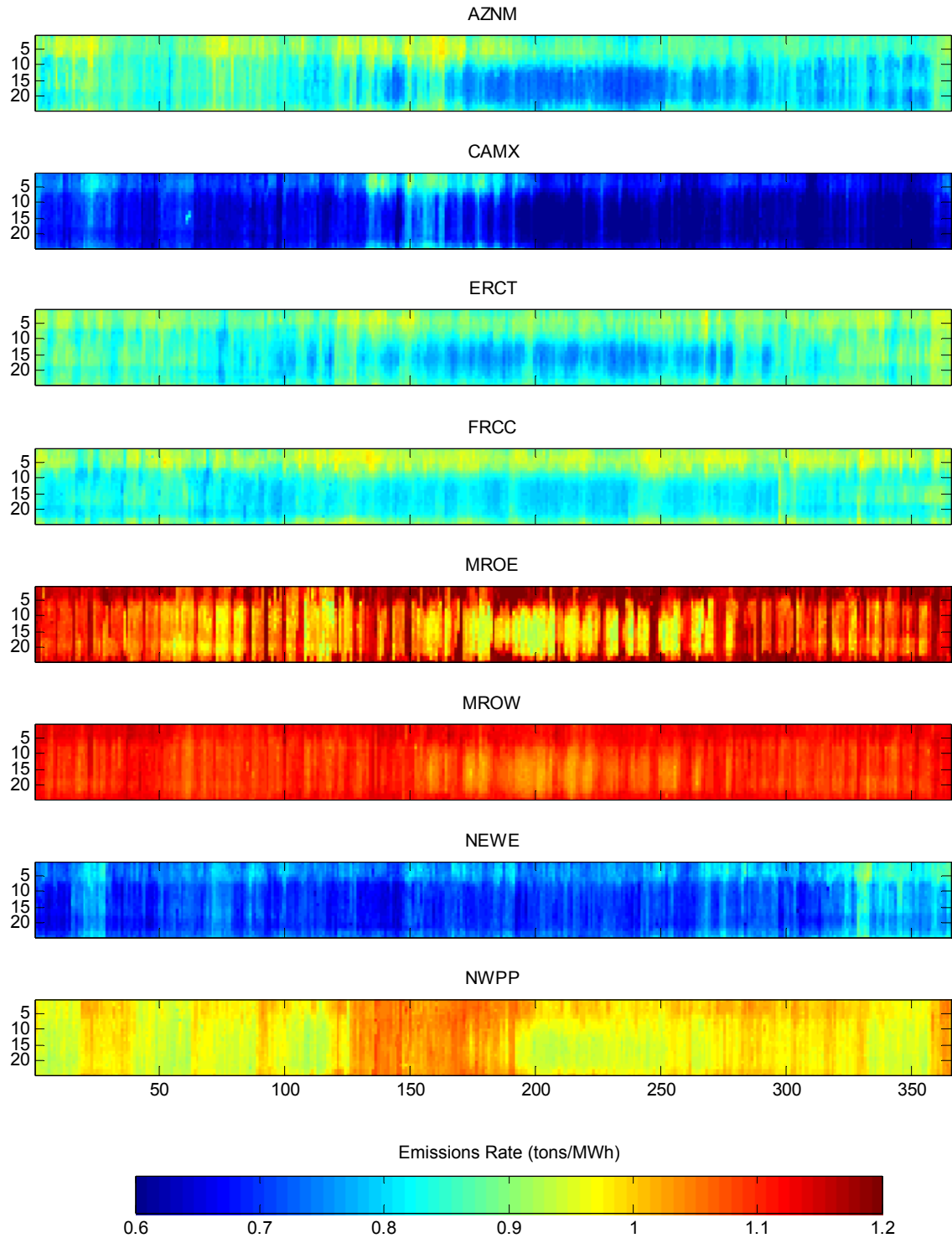
Each grid shows hour of the day on the vertical axis and days of the year on the horizontal axis. Color scale is shown at the bottom of each page.

The indirect emissions metrics shown are:

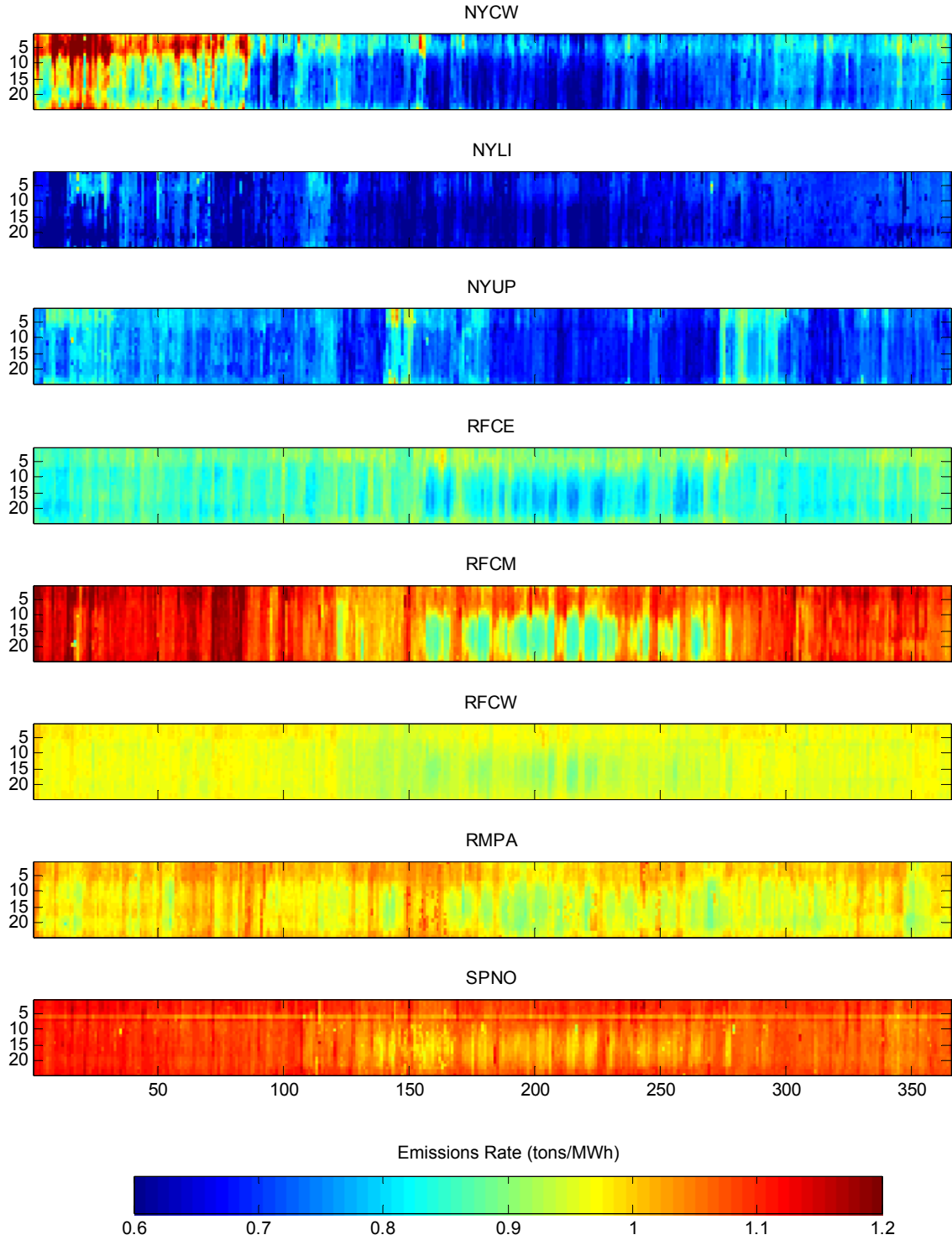
Figure	Title	Page
D-1	Hourly Average CO ₂ Emissions Rate	56
D-2	Empirical Incremental CO ₂ Emissions Rate	59
D-3	Flexibility-Weighted Hourly Average CO ₂ Emissions Rate	62
D-4	Load Following Incremental CO ₂ Emissions Rate	65
D-5	Hourly Average NO _x Emissions Rate	68
D-6	Empirical Incremental NO _x Emissions Rate	71
D-7	Flexibility-Weighted Hourly Average NO _x Emissions Rate	74
D-8	Load Following Incremental NO _x Emissions Rate	77
D-9	Hourly Average SO ₂ Emissions Rate	80
D-10	Empirical Incremental SO ₂ Emissions Rate	83
D-11	Flexibility-Weighted Hourly Average SO ₂ Emissions Rate	86
D-12	Load Following Incremental SO ₂ Emissions Rate	89

The data are available in electronic format upon request.

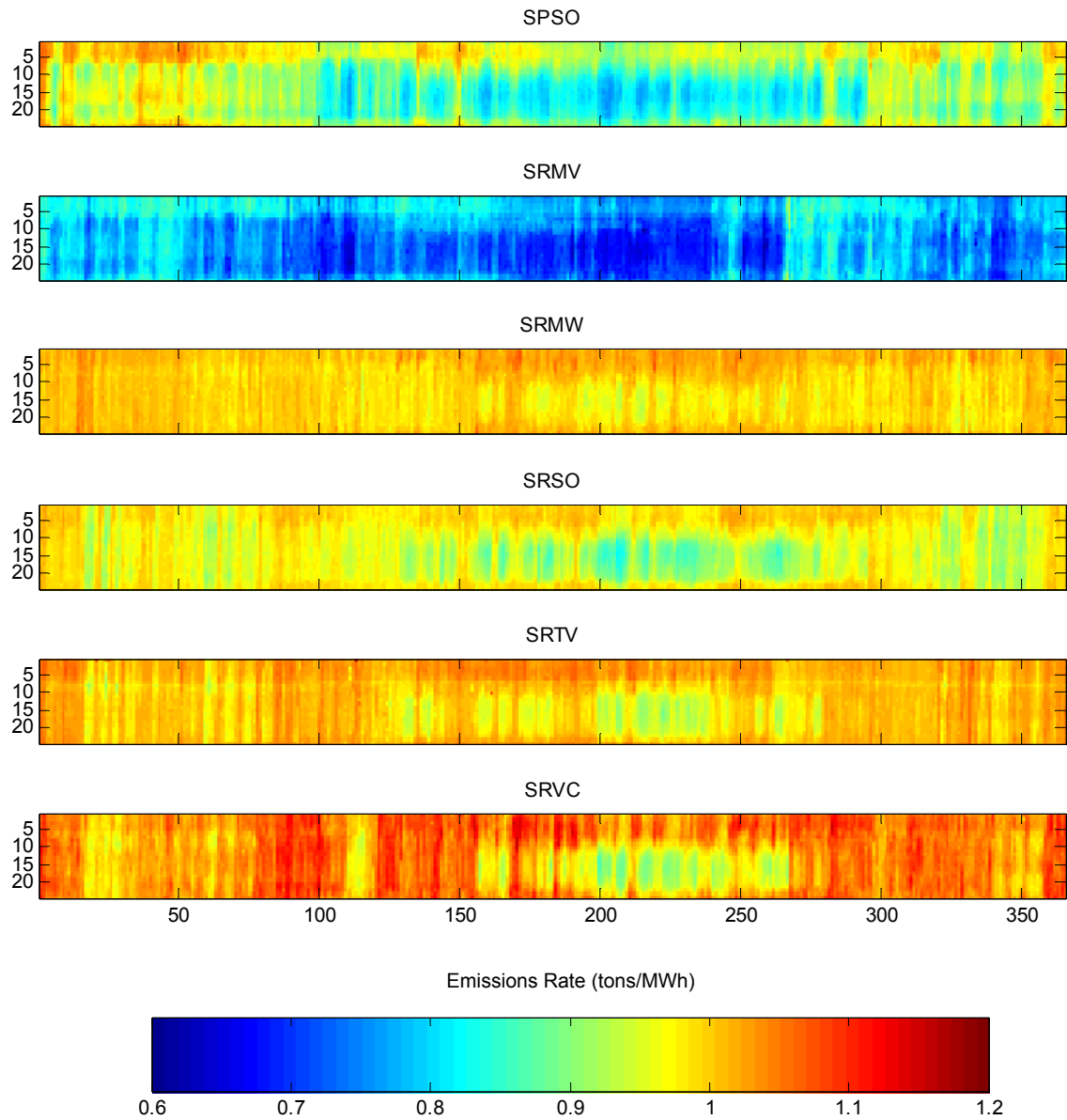
D-1: Hourly Average CO₂ Emissions Rate(tons per MWh)



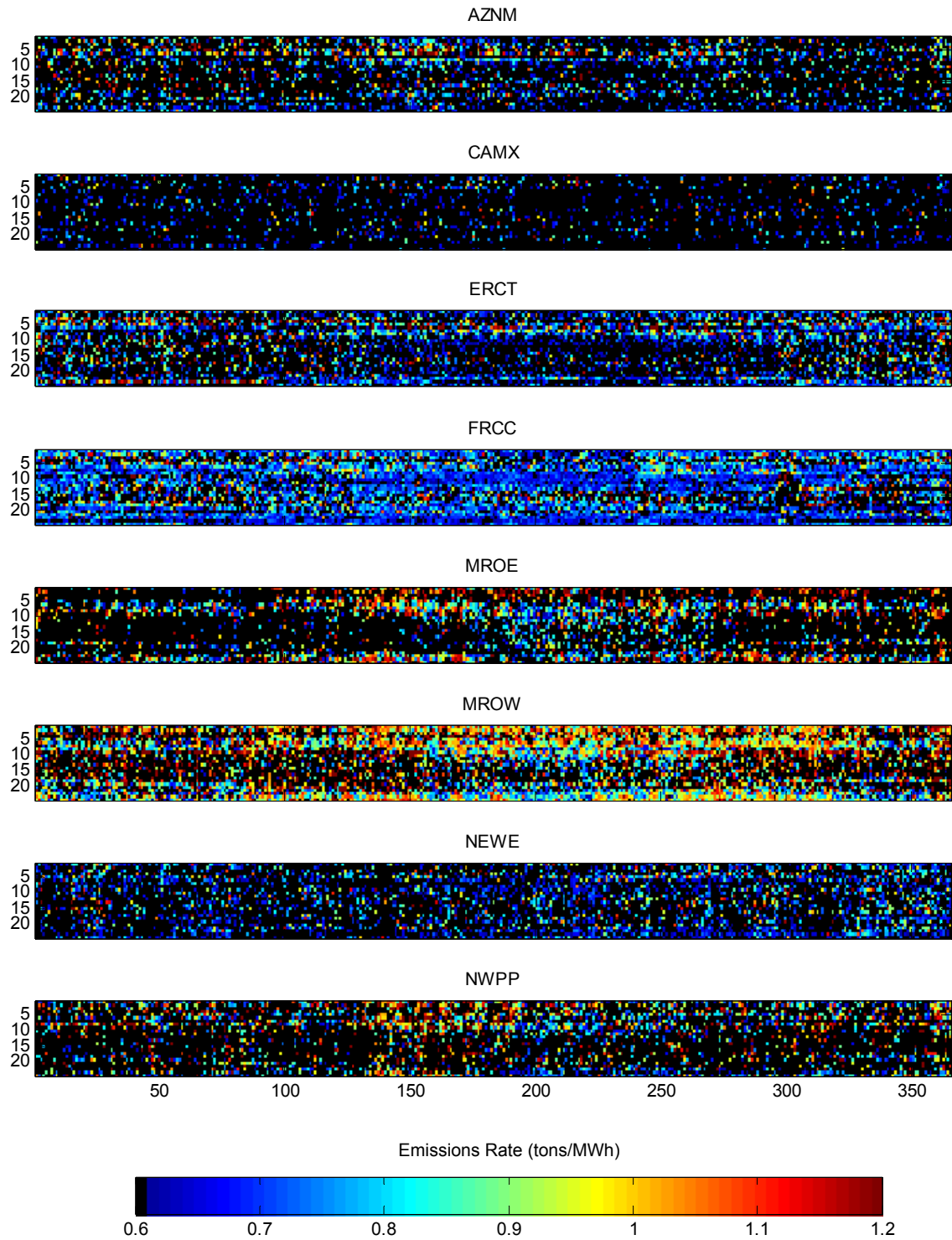
D-1 (continued): Hourly Average CO₂ Emissions Rate



D-1 (continued): Hourly Average CO₂ Emissions Rate (continued)

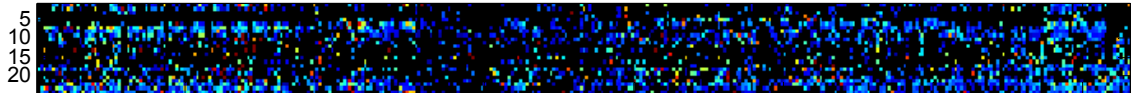


D-2: Empirical Incremental CO₂ Emissions Rate (tons per MWh)

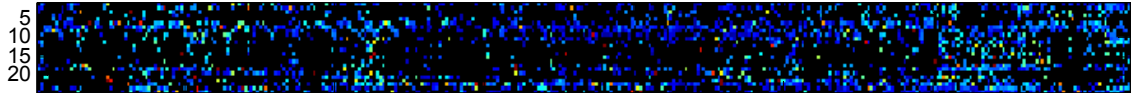


D-2 (continued): Empirical Incremental CO₂ Emissions Rate

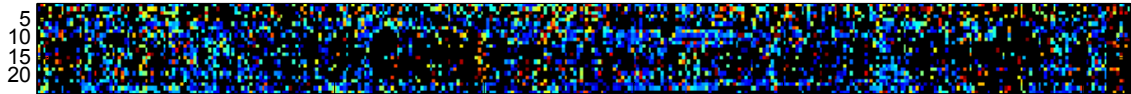
NYCW



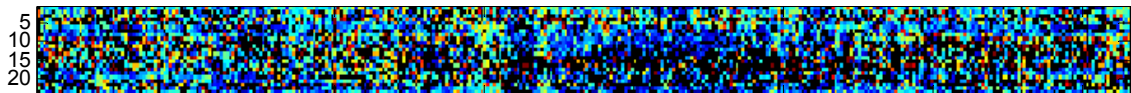
NYLI



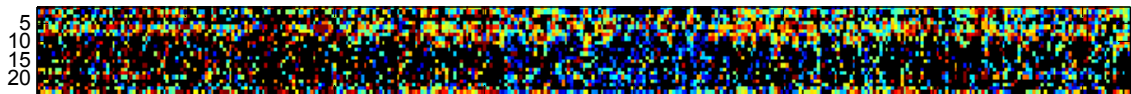
NYUP



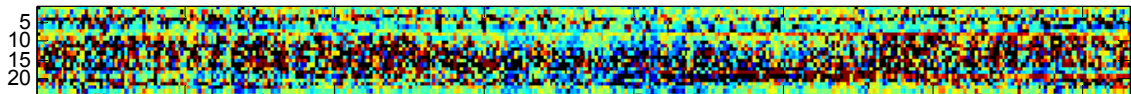
RFCE



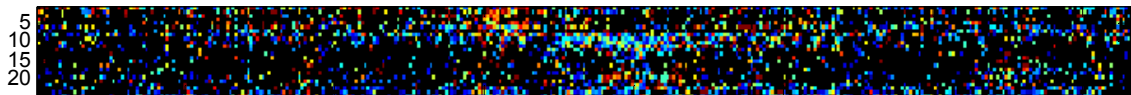
RFCM



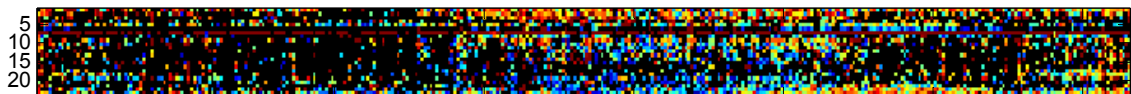
RFCW



RMPA

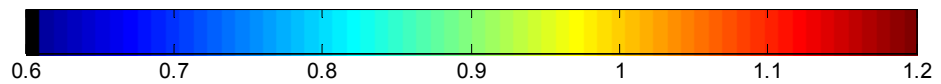


SPNO

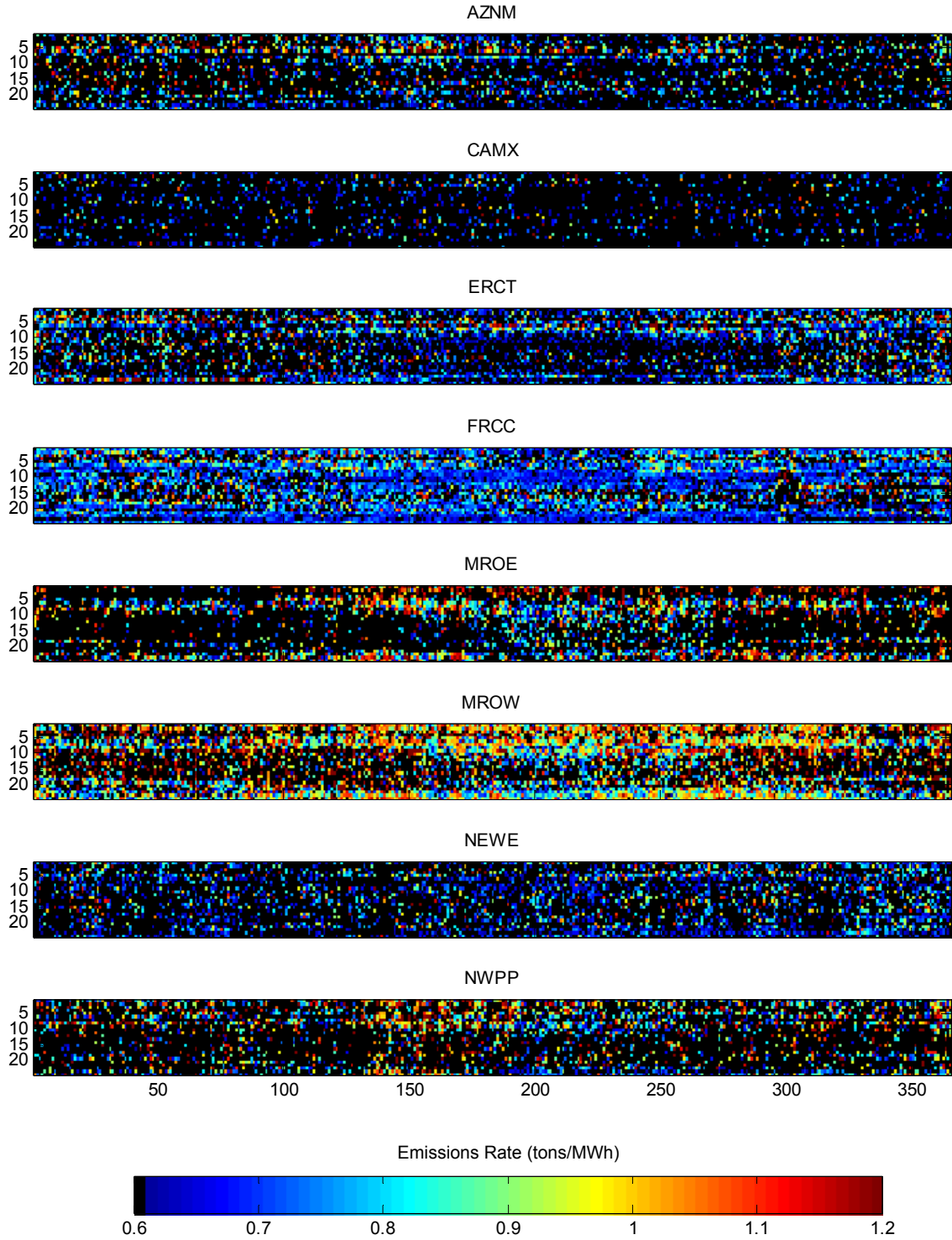


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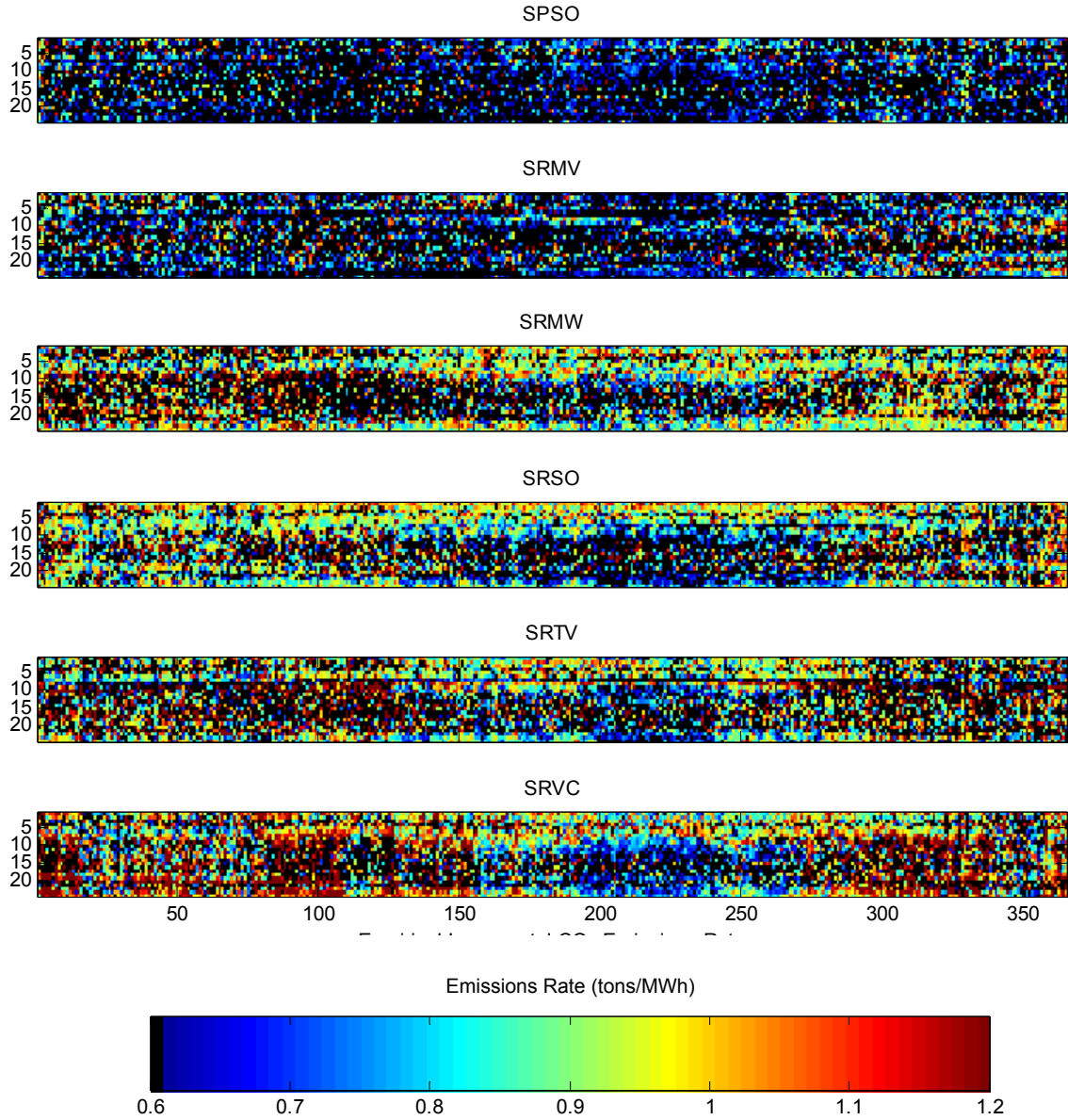
Emissions Rate (tons/MWh)



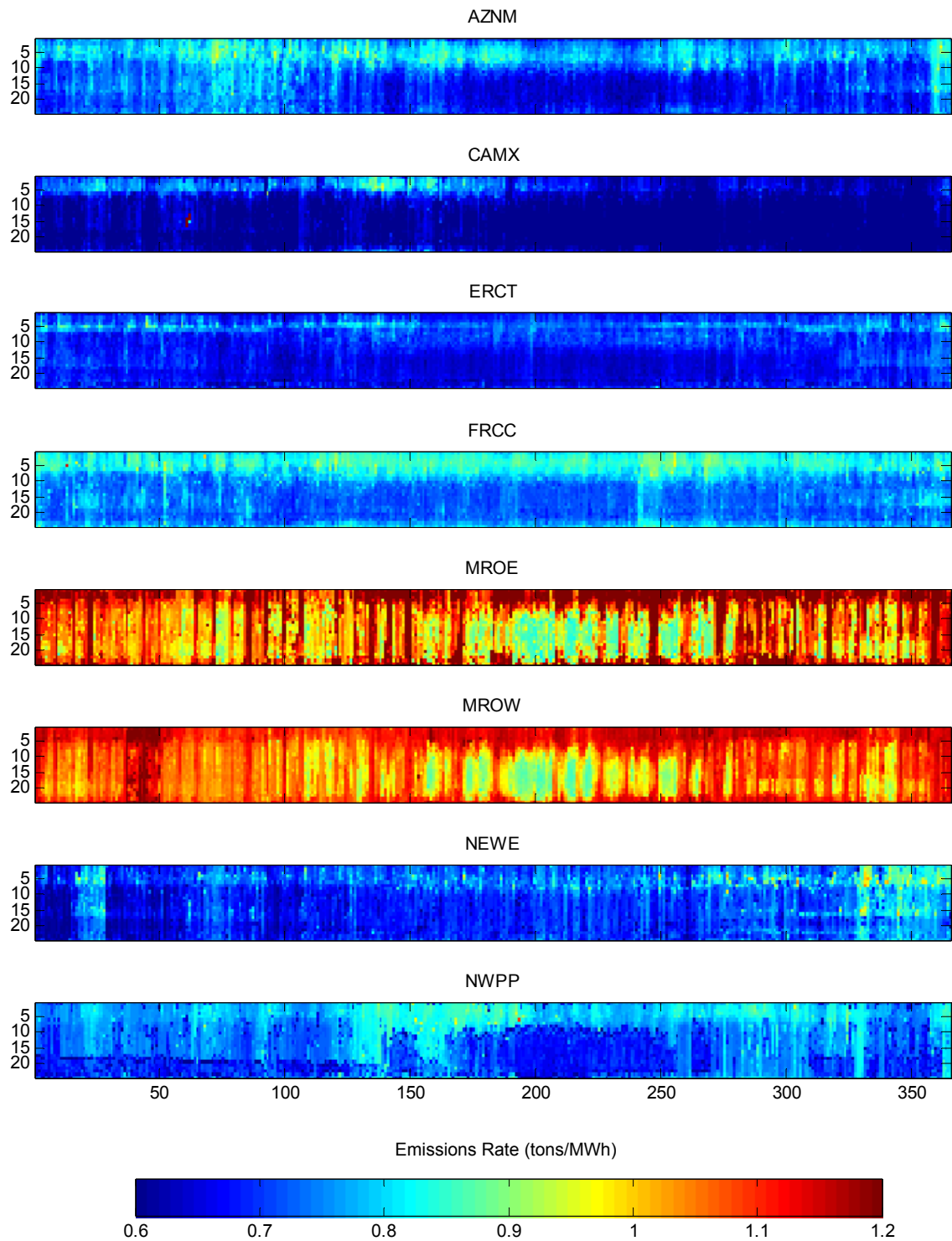
D-2 (continued): Empirical Incremental CO₂ Emissions Rate



D-2 (continued): Empirical Incremental CO₂ Emissions Rate

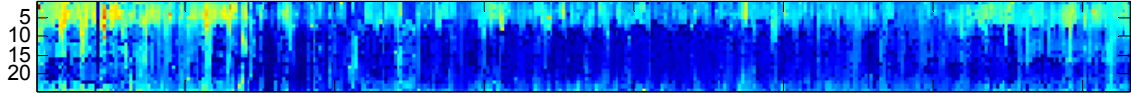


D-3: Flexibility-Weighted Hourly Average CO₂ Emissions Rate (tons per MWh)

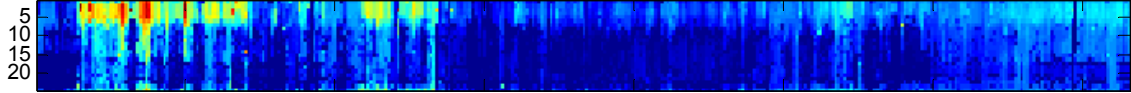


D-3 (continued): Flexibility-Weighted Hourly Average CO₂ Emissions Rate

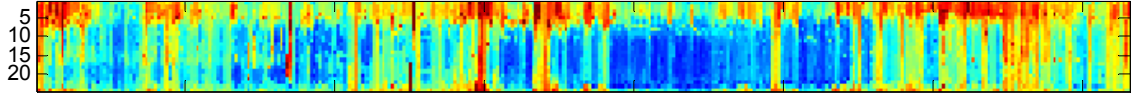
NYCW



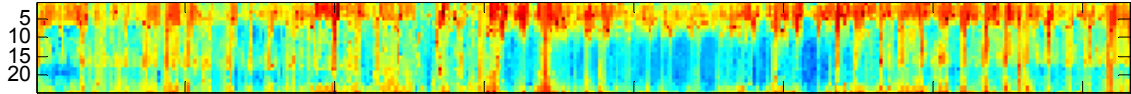
NYLI



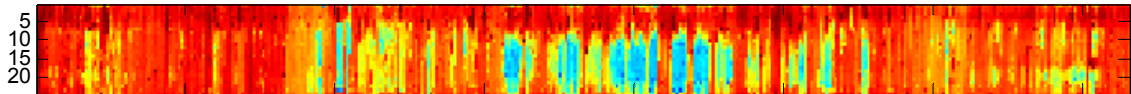
NYUP



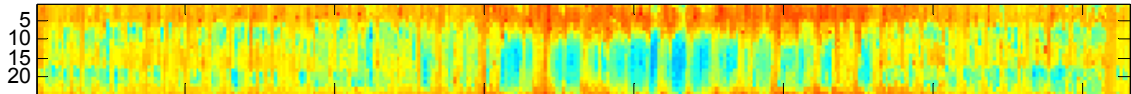
RFCE



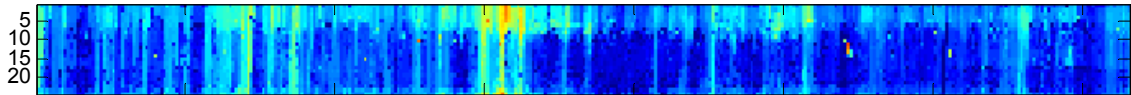
RFCM



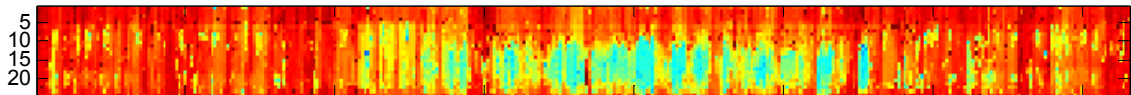
RFCW



RMPA

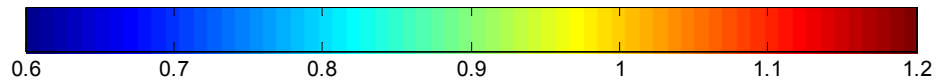


SPNO

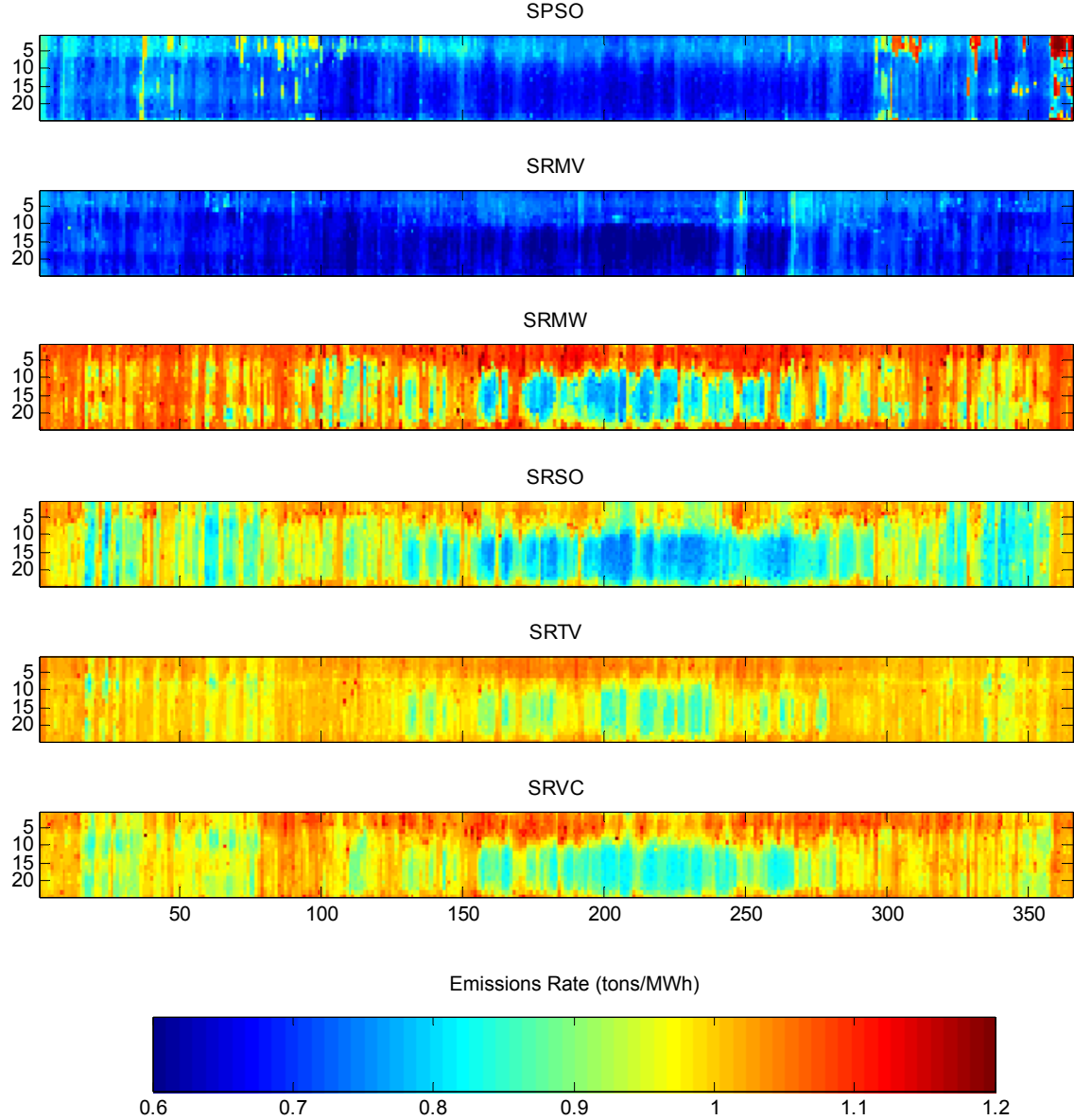


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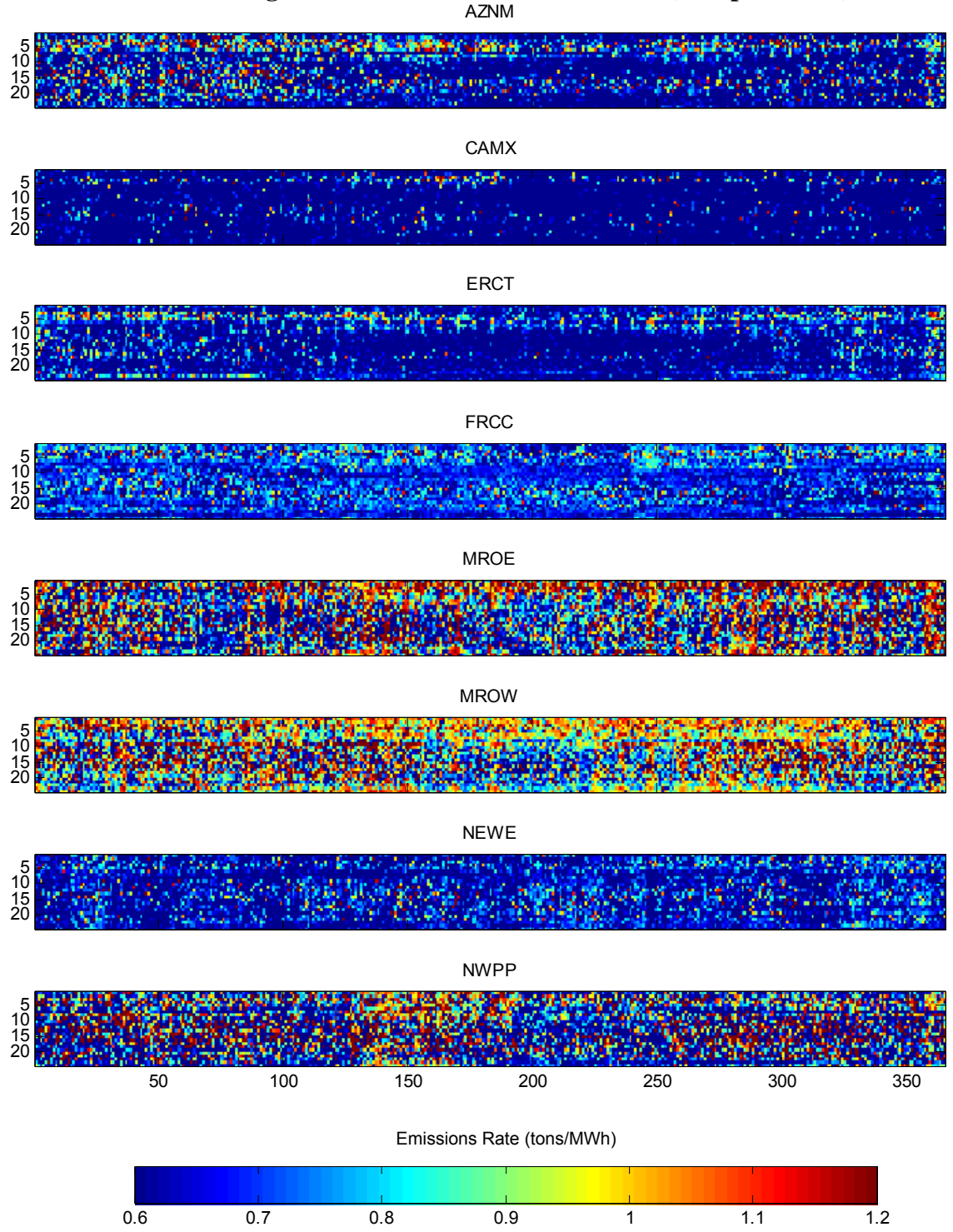
Emissions Rate (tons/MWh)



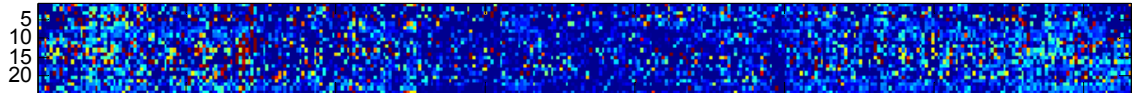
D-3 (continued): Flexibility Weighted Hourly Average CO₂ Emissions Rate



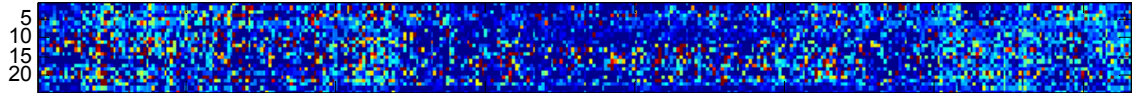
D-4: Load-Following Incremental CO₂ Emissions Rate (tons per MWh)



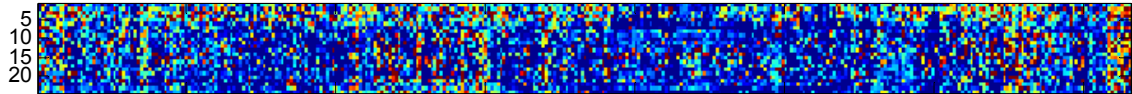
D-4 (continued): Load-Following Incremental CO₂ Emissions Rate NYCW



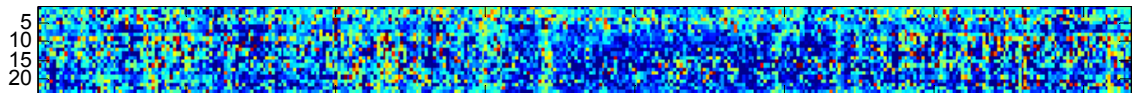
NYLI



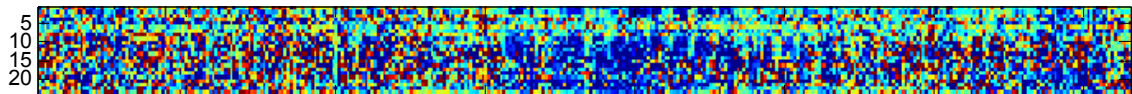
NYUP



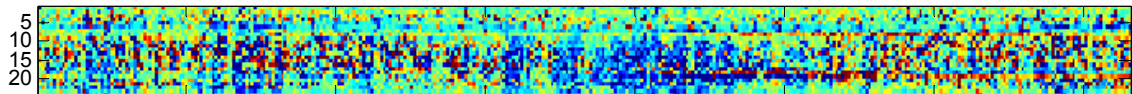
RFCE



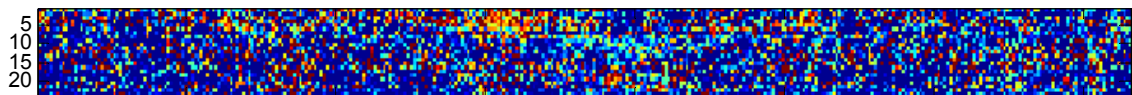
RFCM



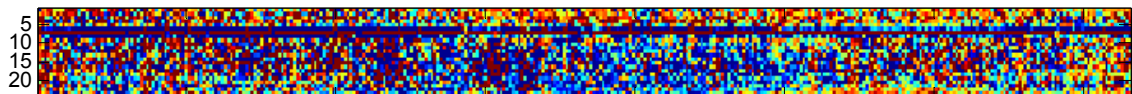
RFCW



RMPA

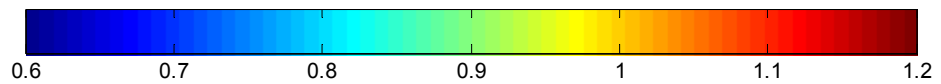


SPNO

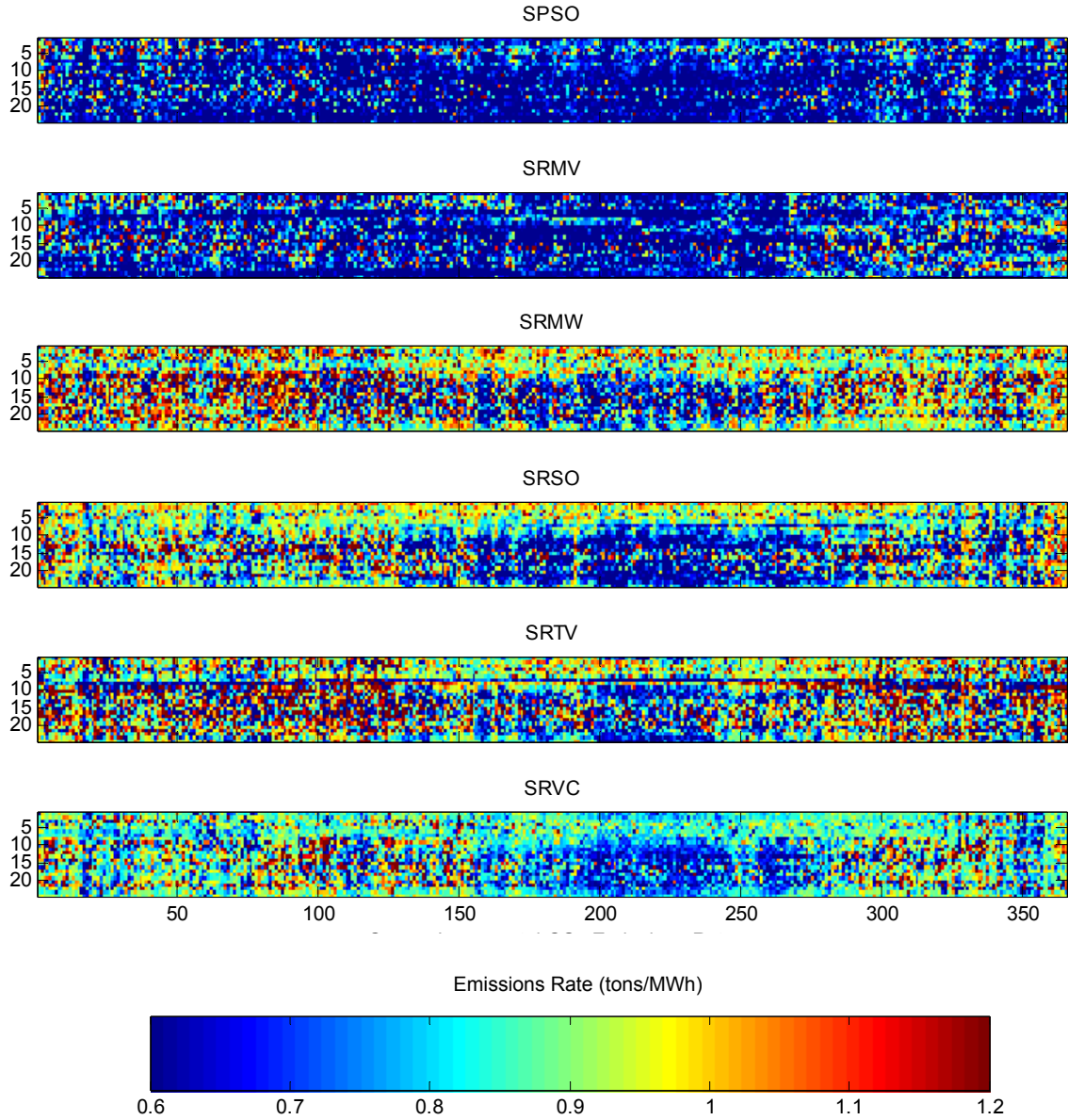


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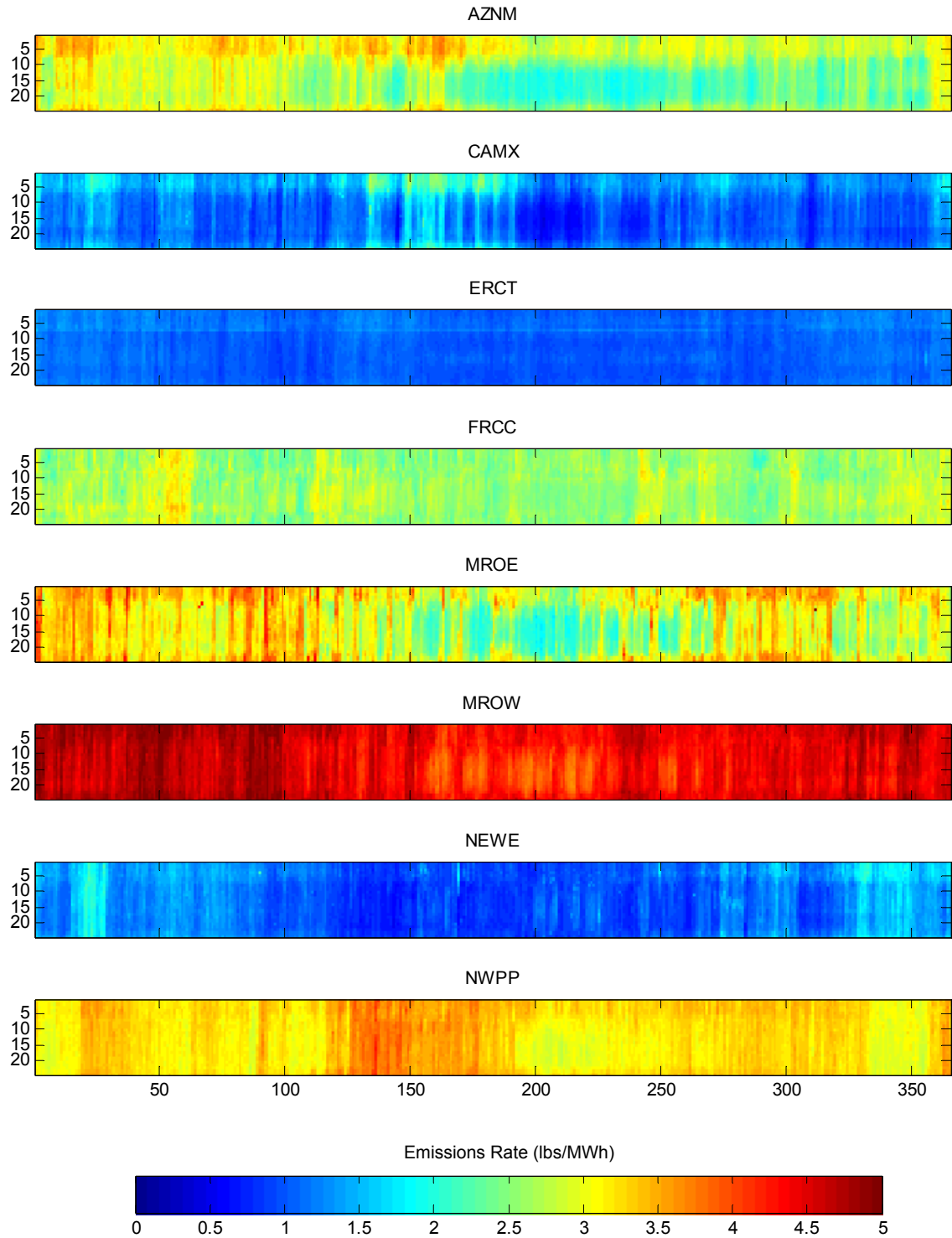
Emissions Rate (tons/MWh)



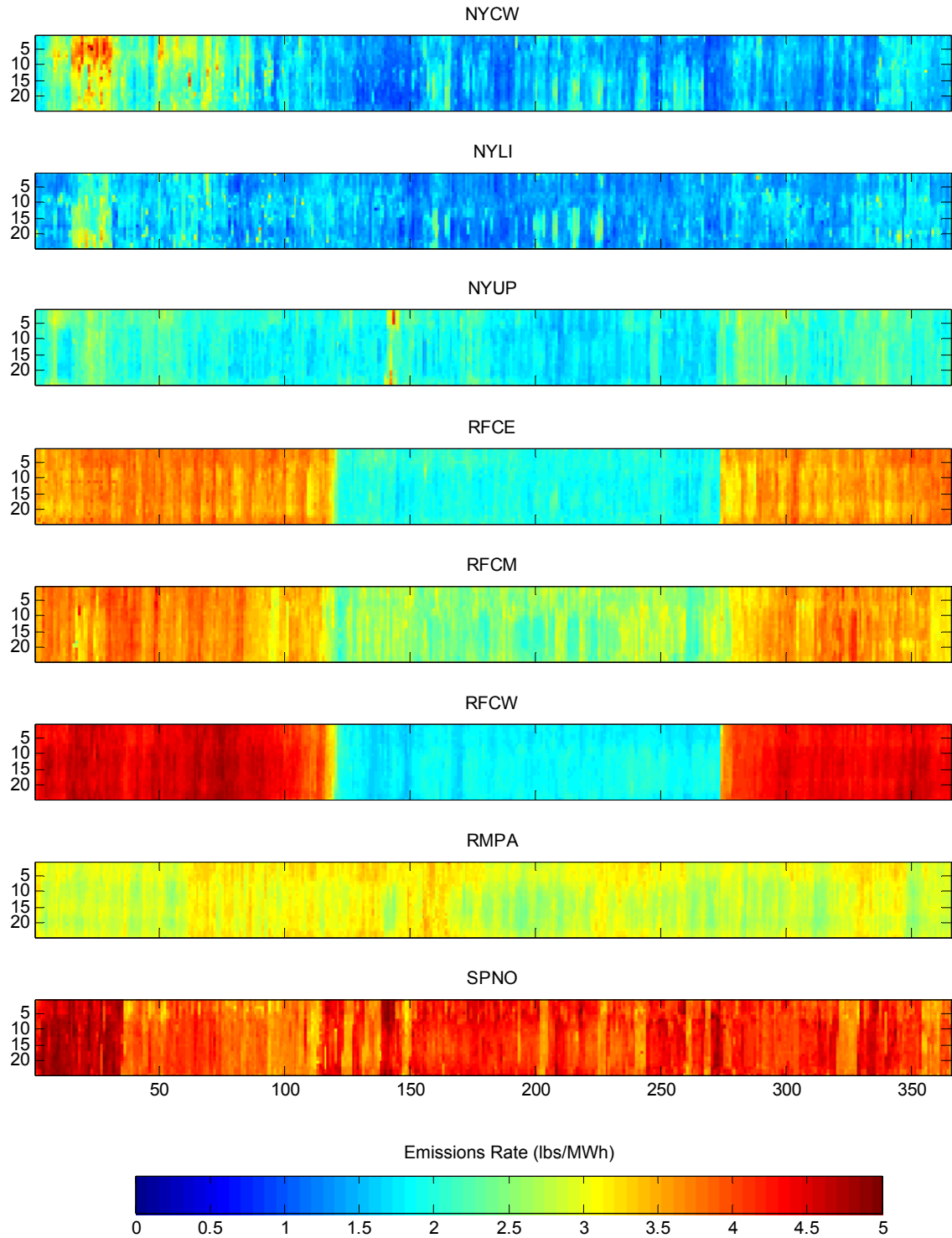
D-4 (continued): Load-Following Incremental CO₂ Emissions Rate



D-5: Hourly Average NOx Emissions Rate (pounds per MWh)

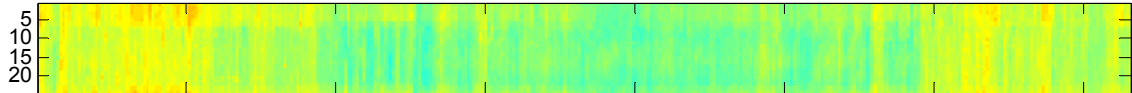


D-5 (continued): Hourly Average NOx Emissions Rate

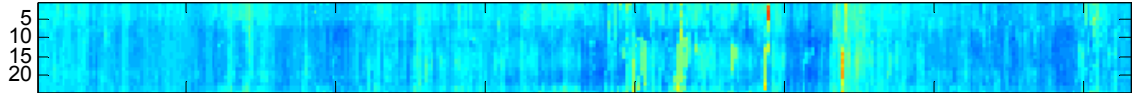


D-5 (continued): Hourly Average NOx Emissions Rate

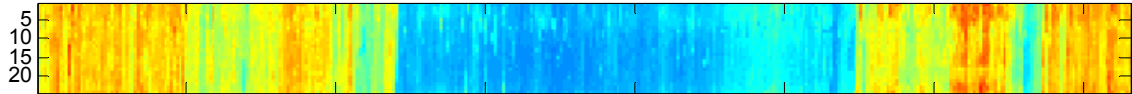
SPSO



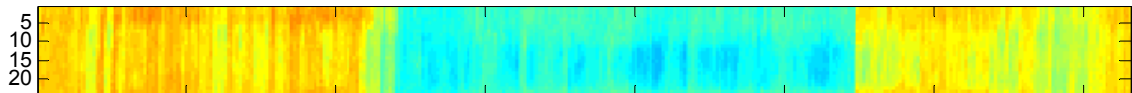
SRMV



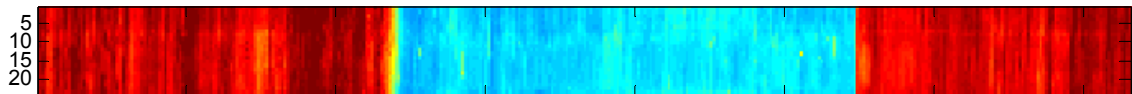
SRMW



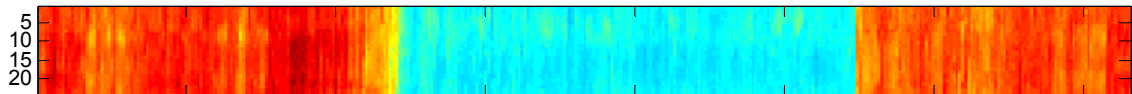
SRSO



SRTV

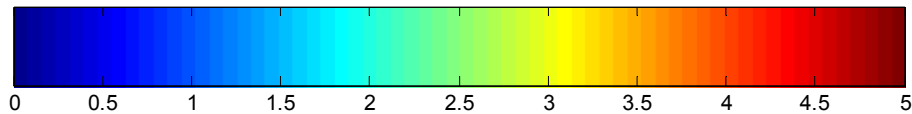


SRVC

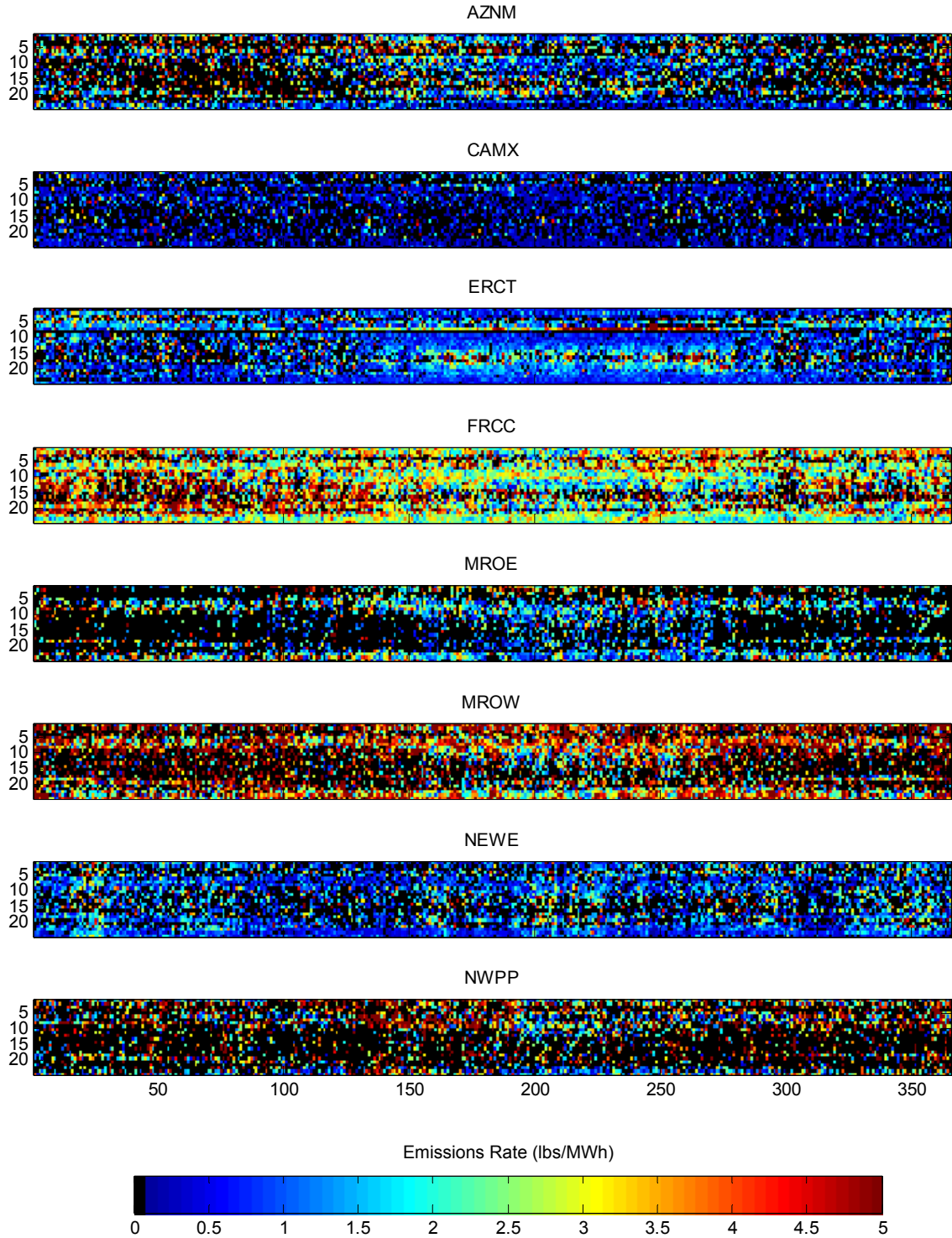


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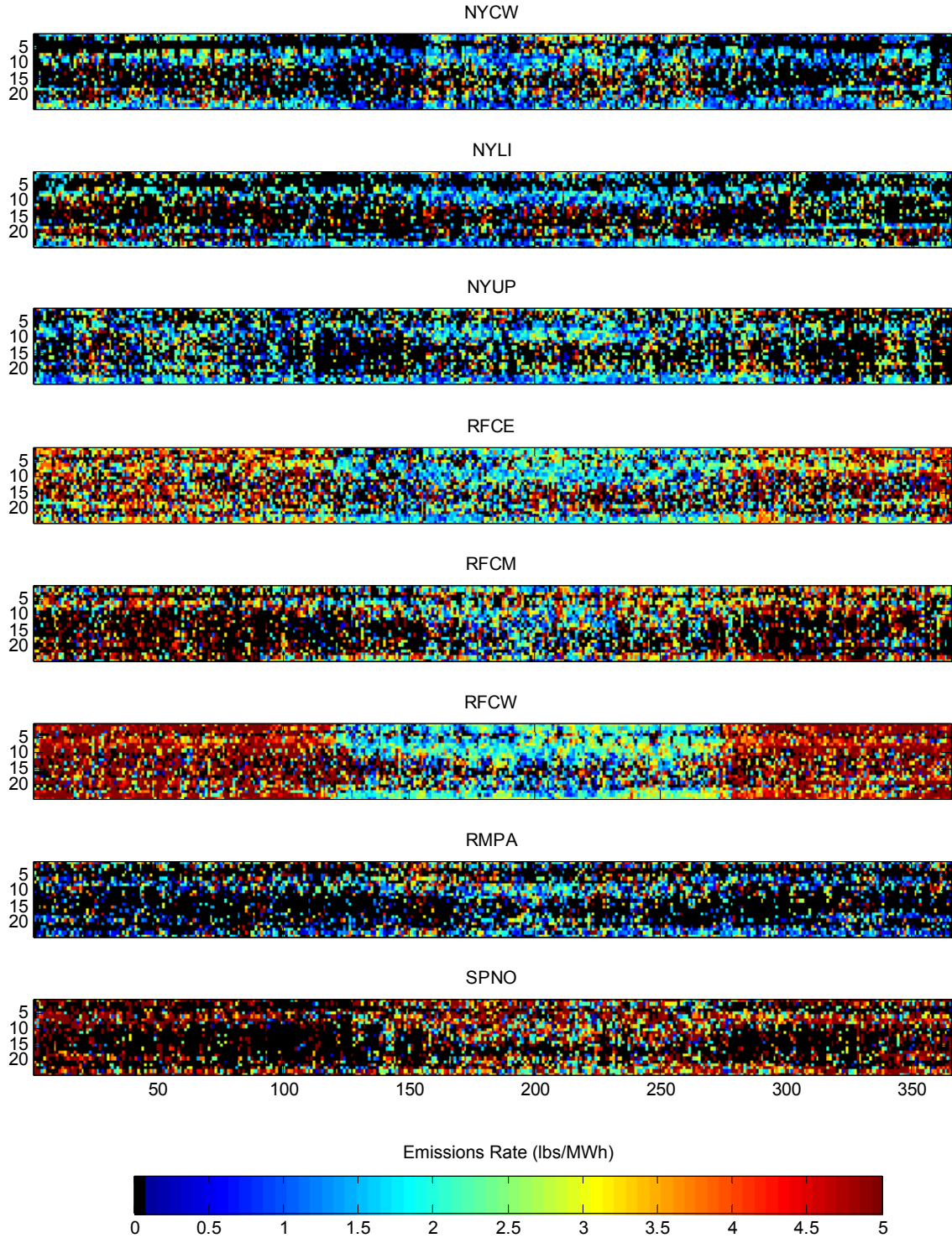
Emissions Rate (lbs/MWh)



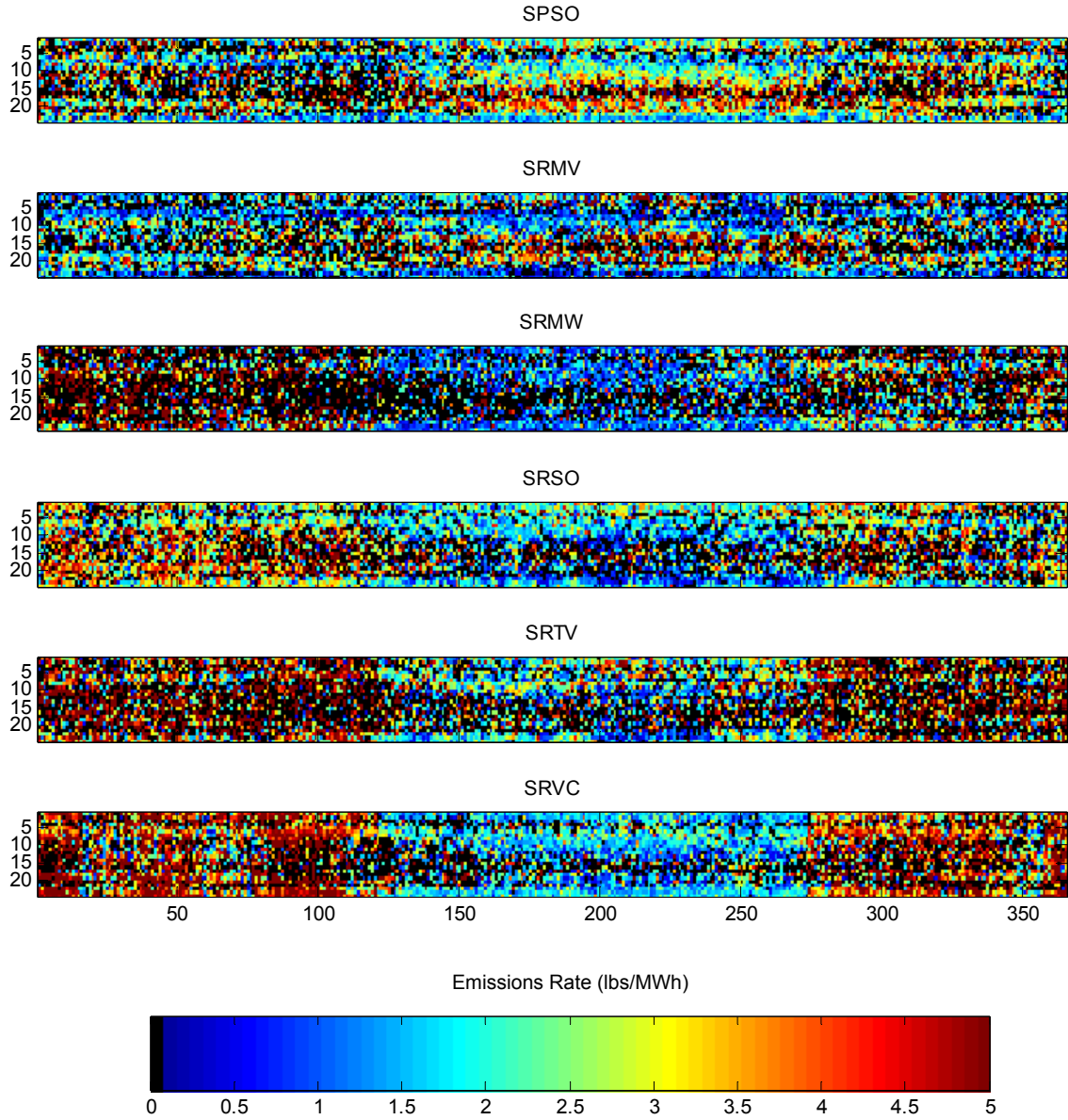
D-6: Empirical Incremental NOx Emissions Rate (pounds per MWh)



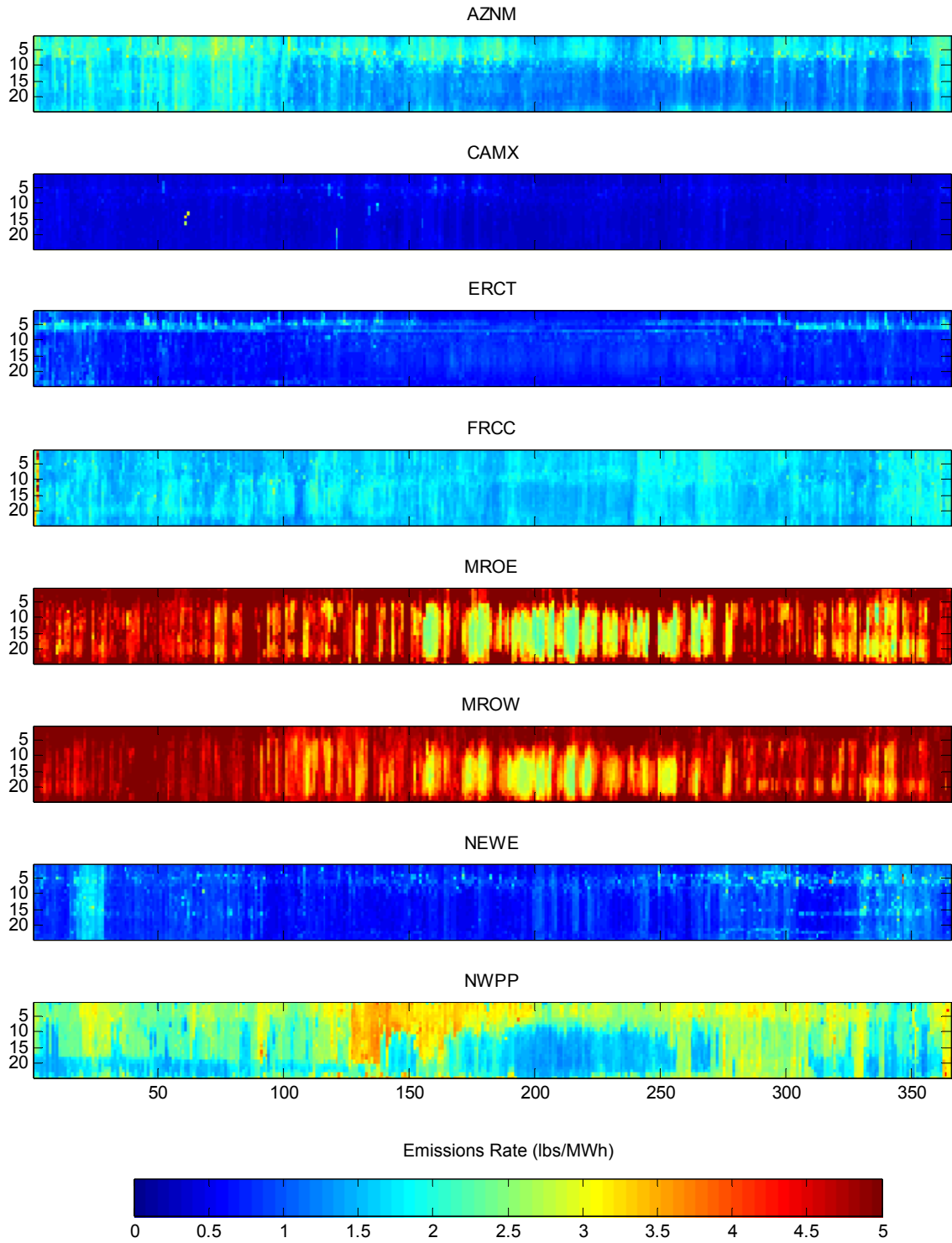
D-6 (continued): Empirical Incremental NOx Emissions Rate



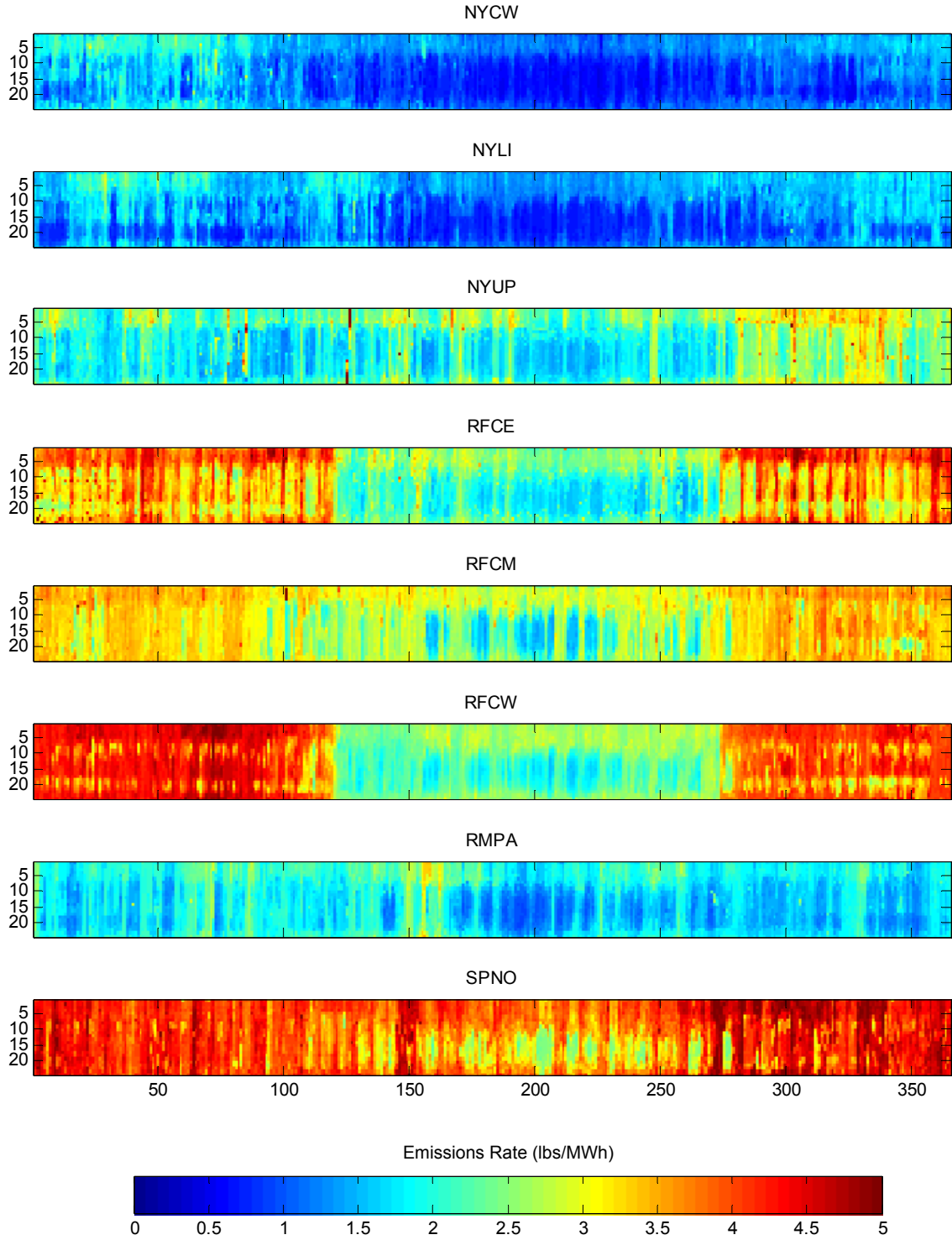
D-6 (continued): Empirical Incremental NOx Emissions Rate



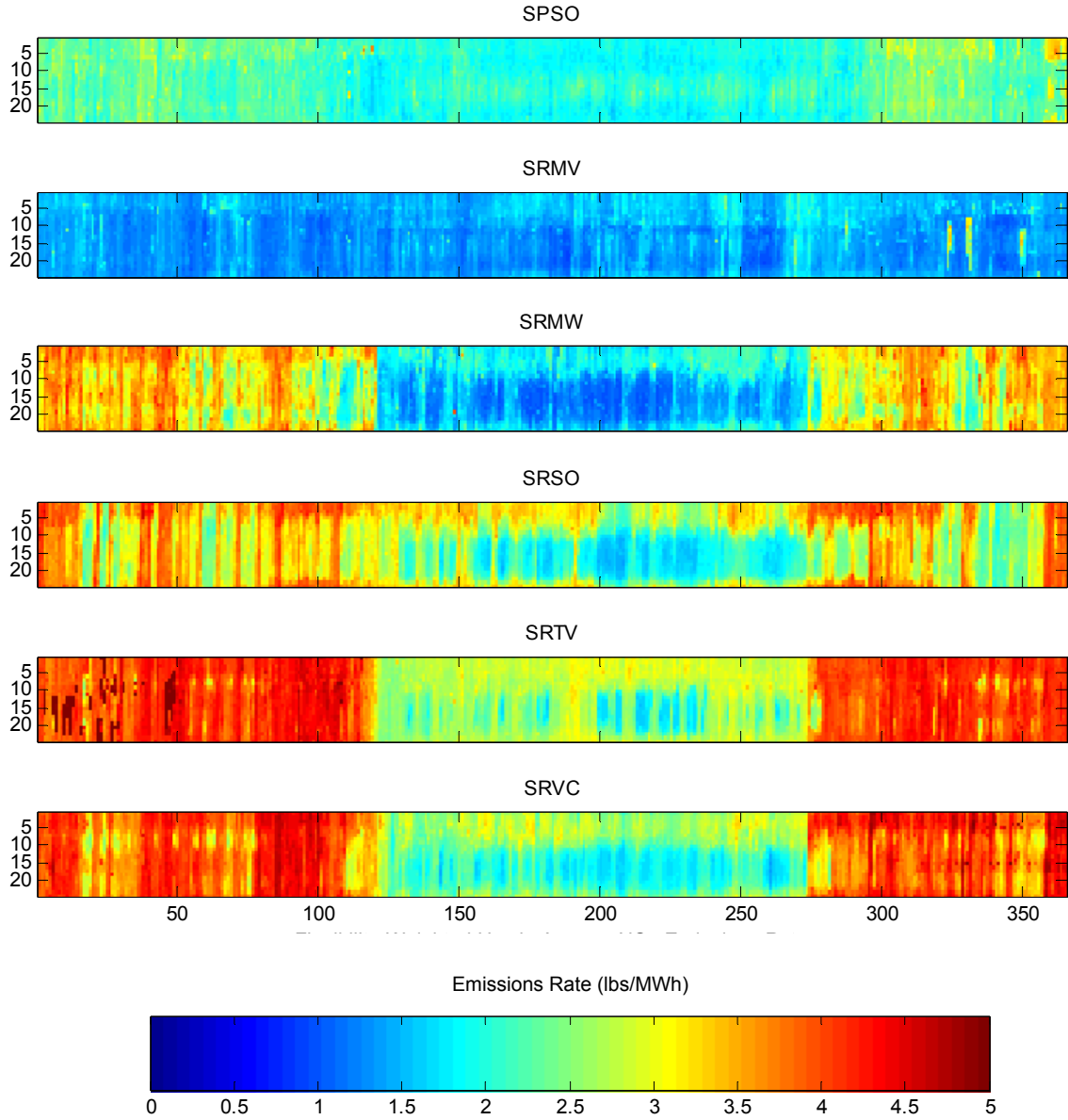
D-7: Flexibility-Weighted Hourly Average NOx Emissions Rate (pounds per MWh)



D-7 (continued): Flexibility-Weighted Hourly Average NOx Emissions Rate

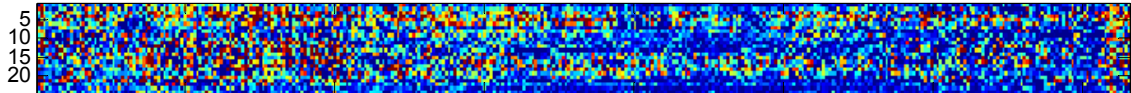


D-7 (continued): Flexibility-Weighted Hourly Average NOx Emissions Rate

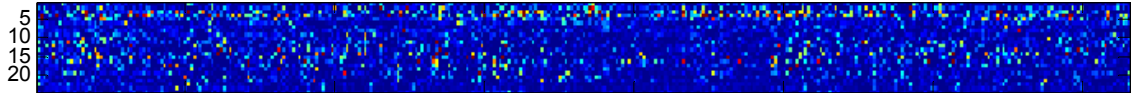


D-8: Load-Following Incremental NOx Emissions Rate (pounds per MWh)

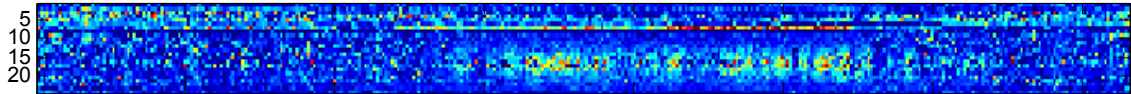
AZNM



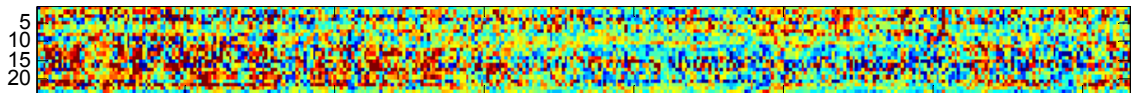
CAMX



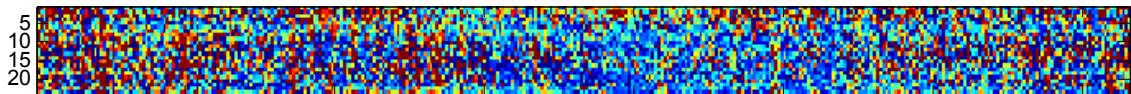
ERCT



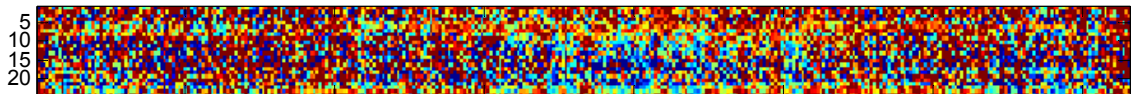
FRCC



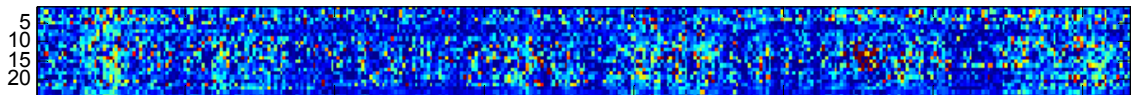
MROE



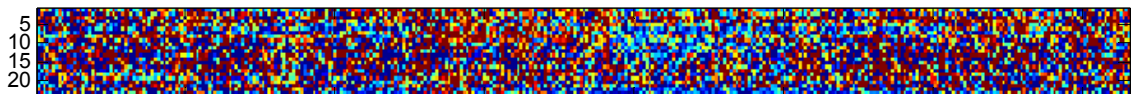
MROW



NEWE

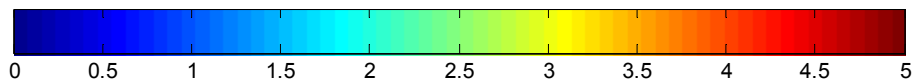


NWPP

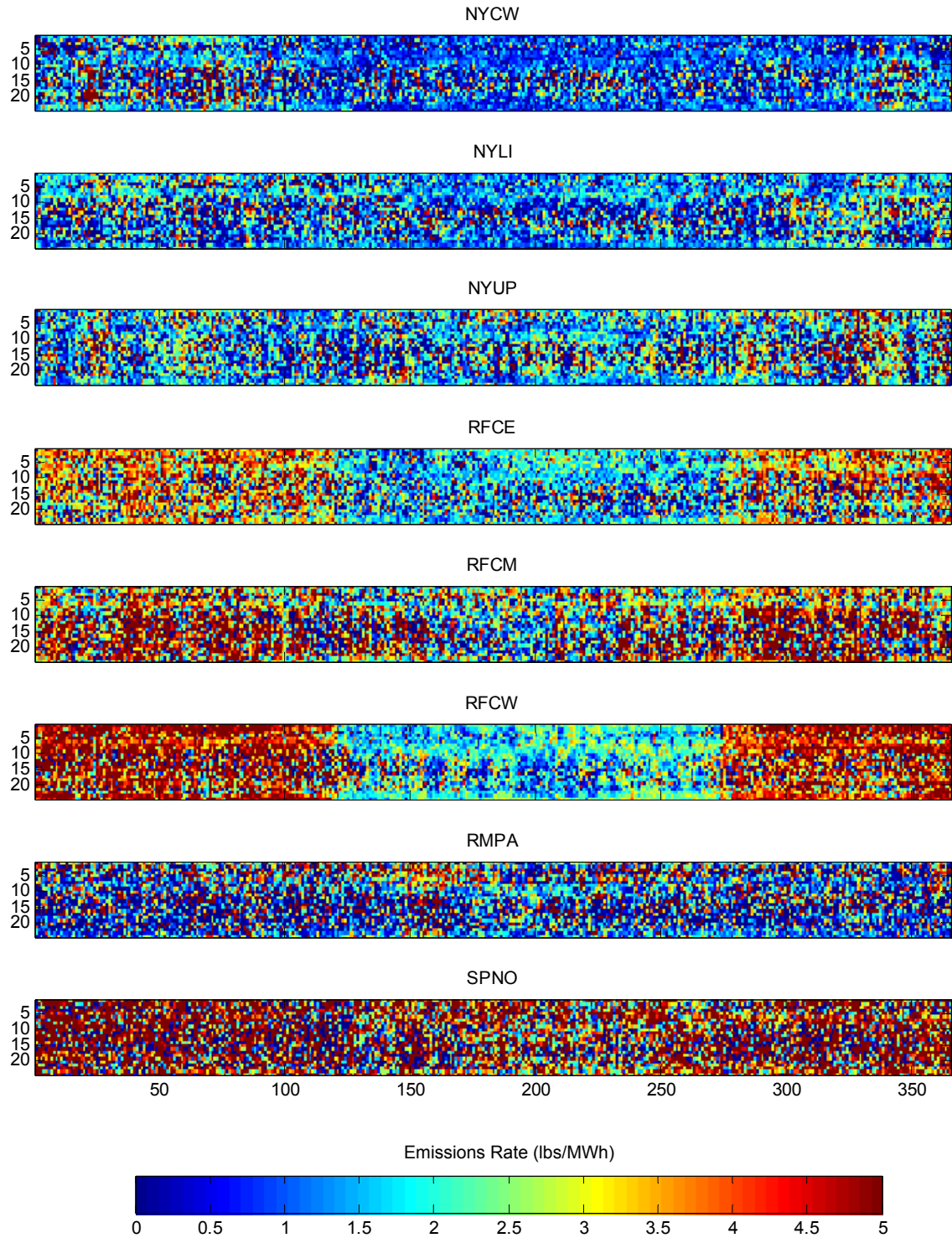


50 100 150 200 250 300 350

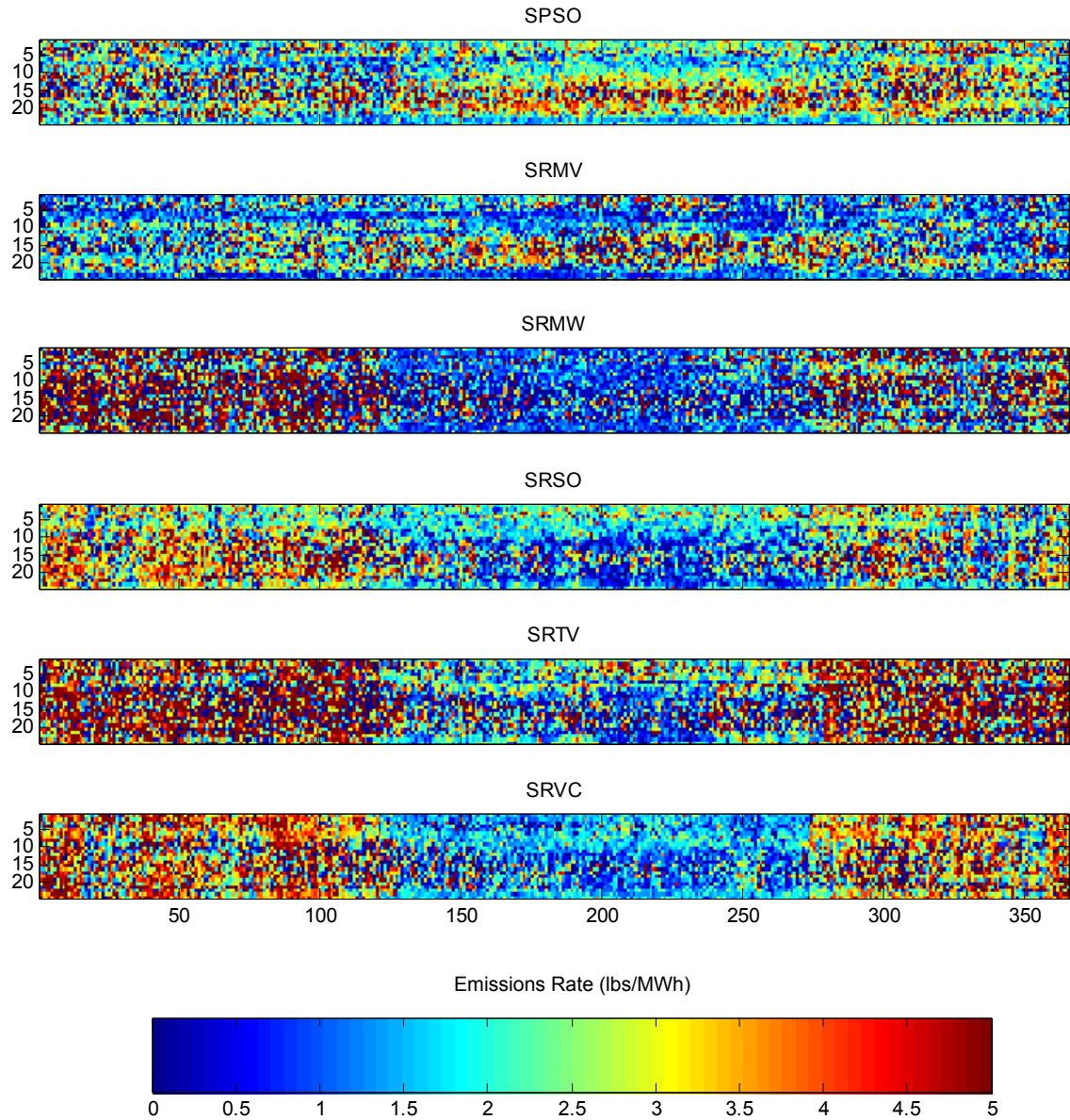
Emissions Rate (lbs/MWh)



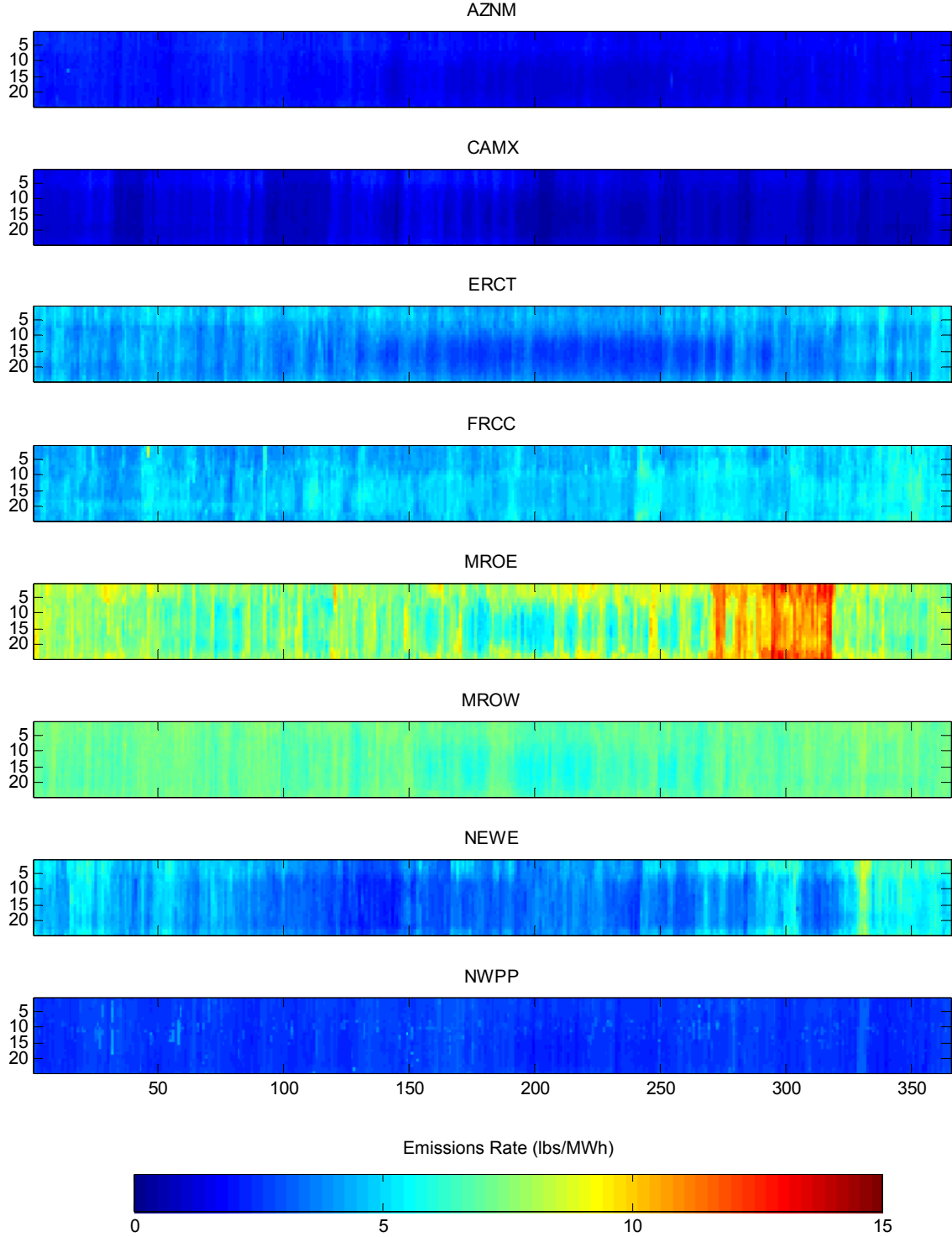
D-8 (continued): Load-Following Incremental NOx Emissions Rate



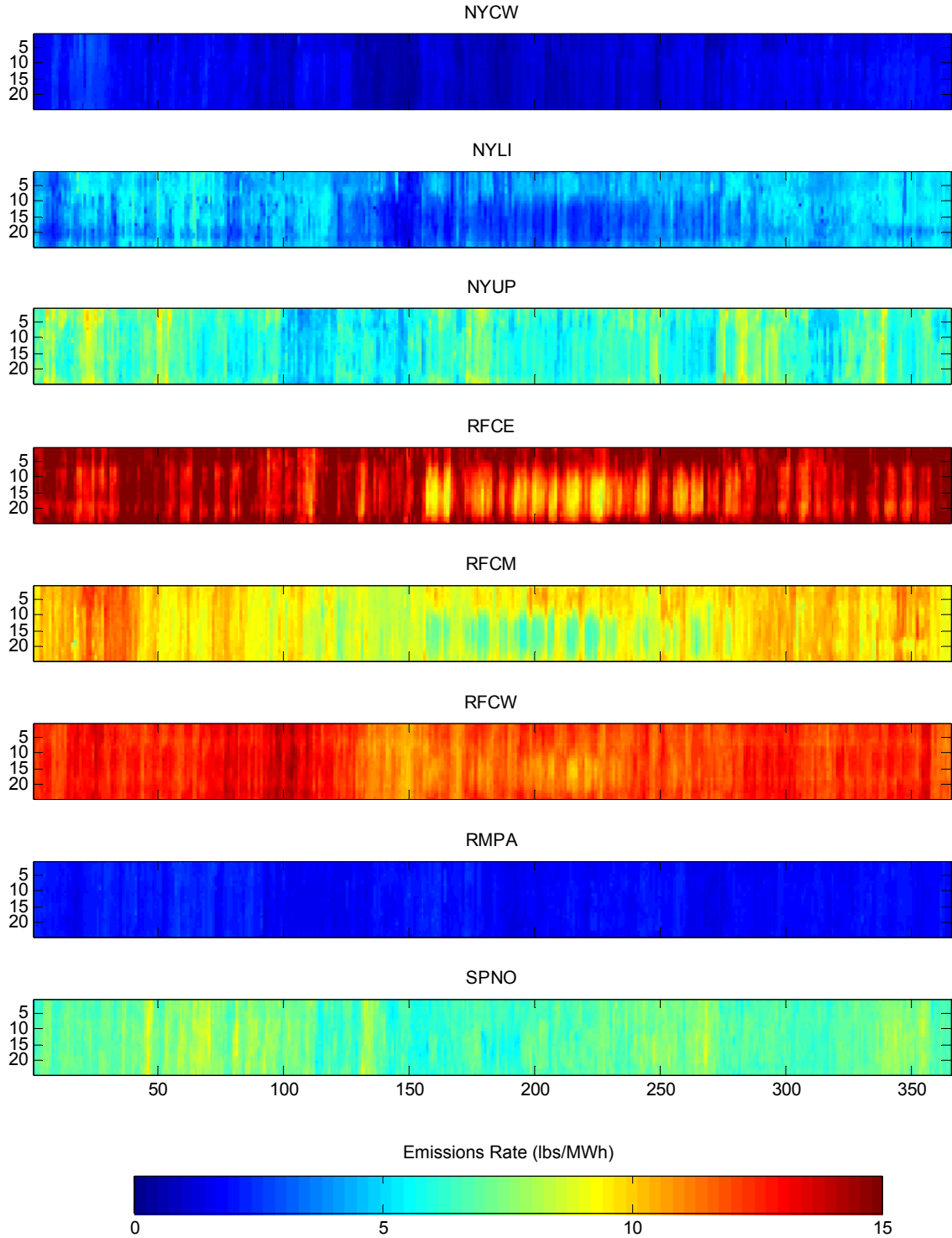
D-8 (continued): Load-Following Incremental NOx Emissions Rate



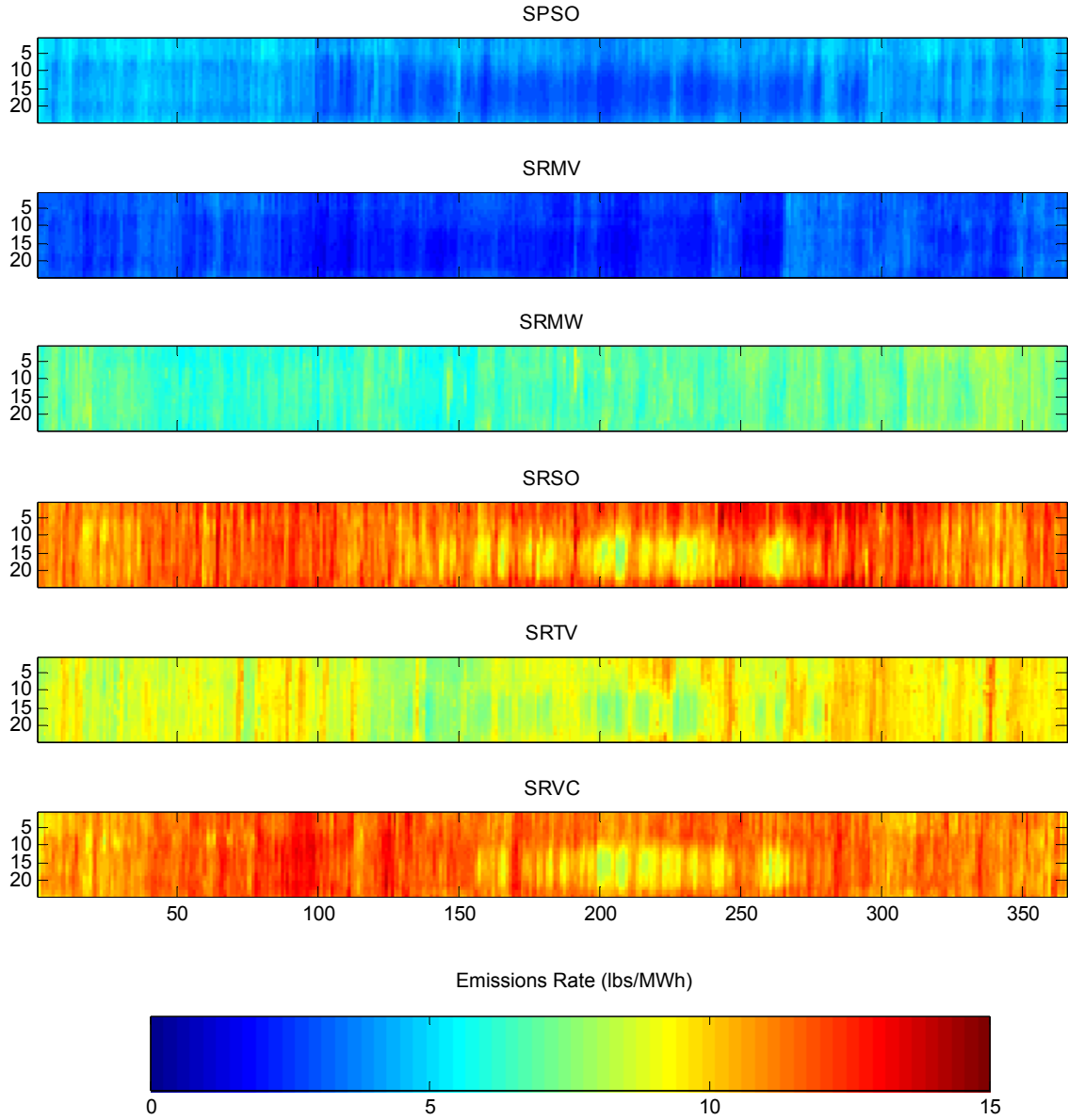
D-9: Hourly Average SO₂ Emissions Rate (pounds per MWh)



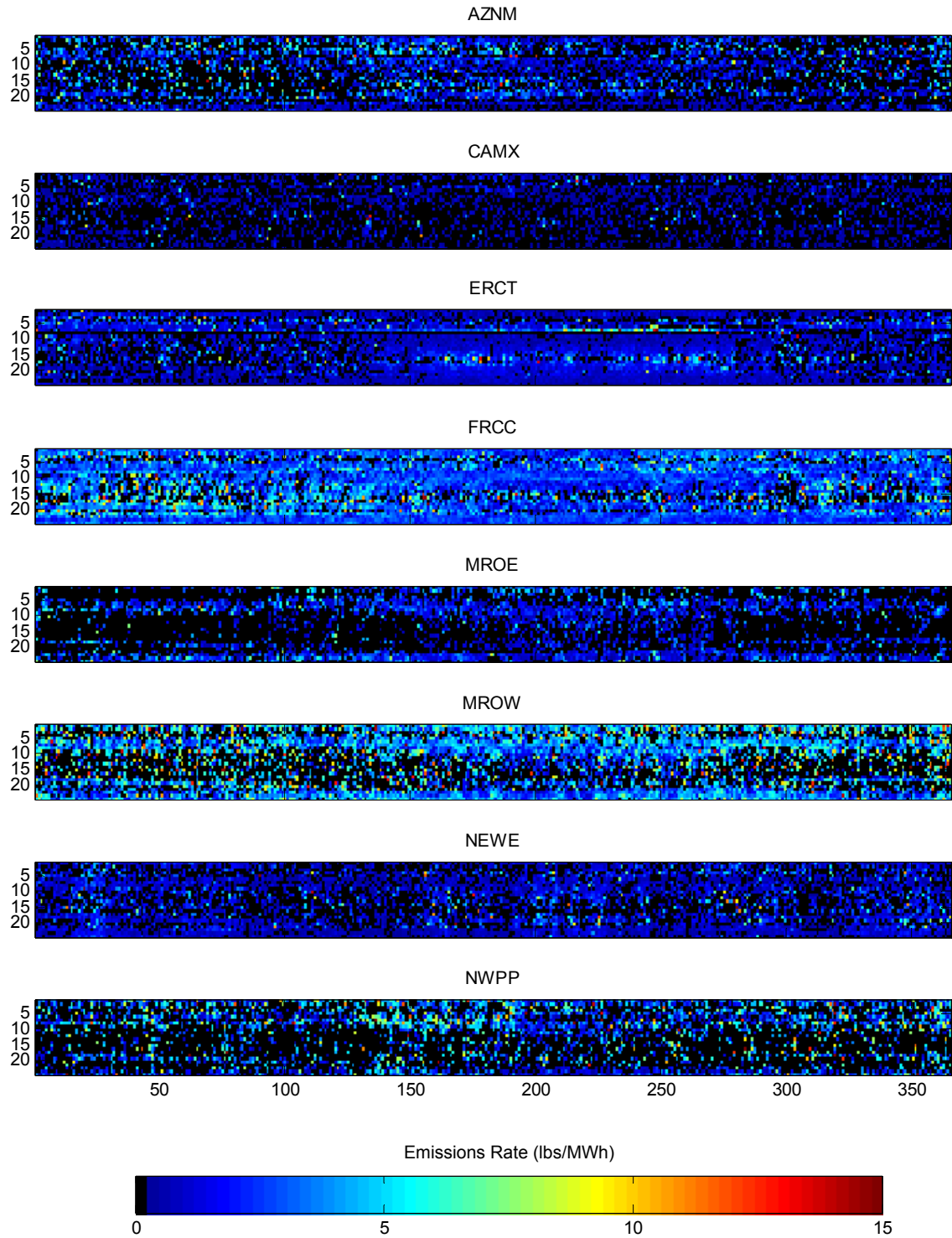
D-9 (continued): Hourly Average SO₂ Emissions Rate



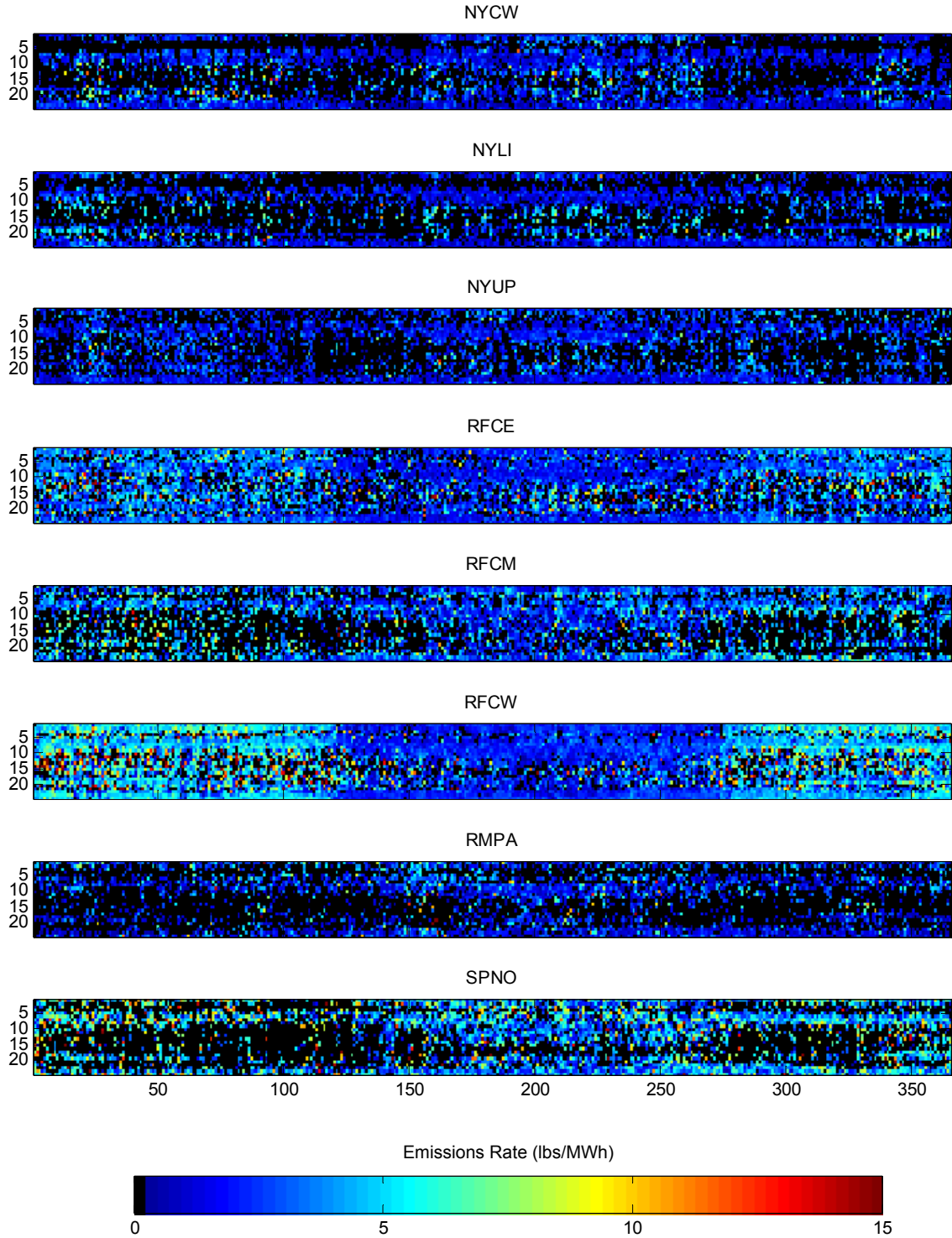
D-9 (continued): Hourly Average SO₂ Emissions Rate



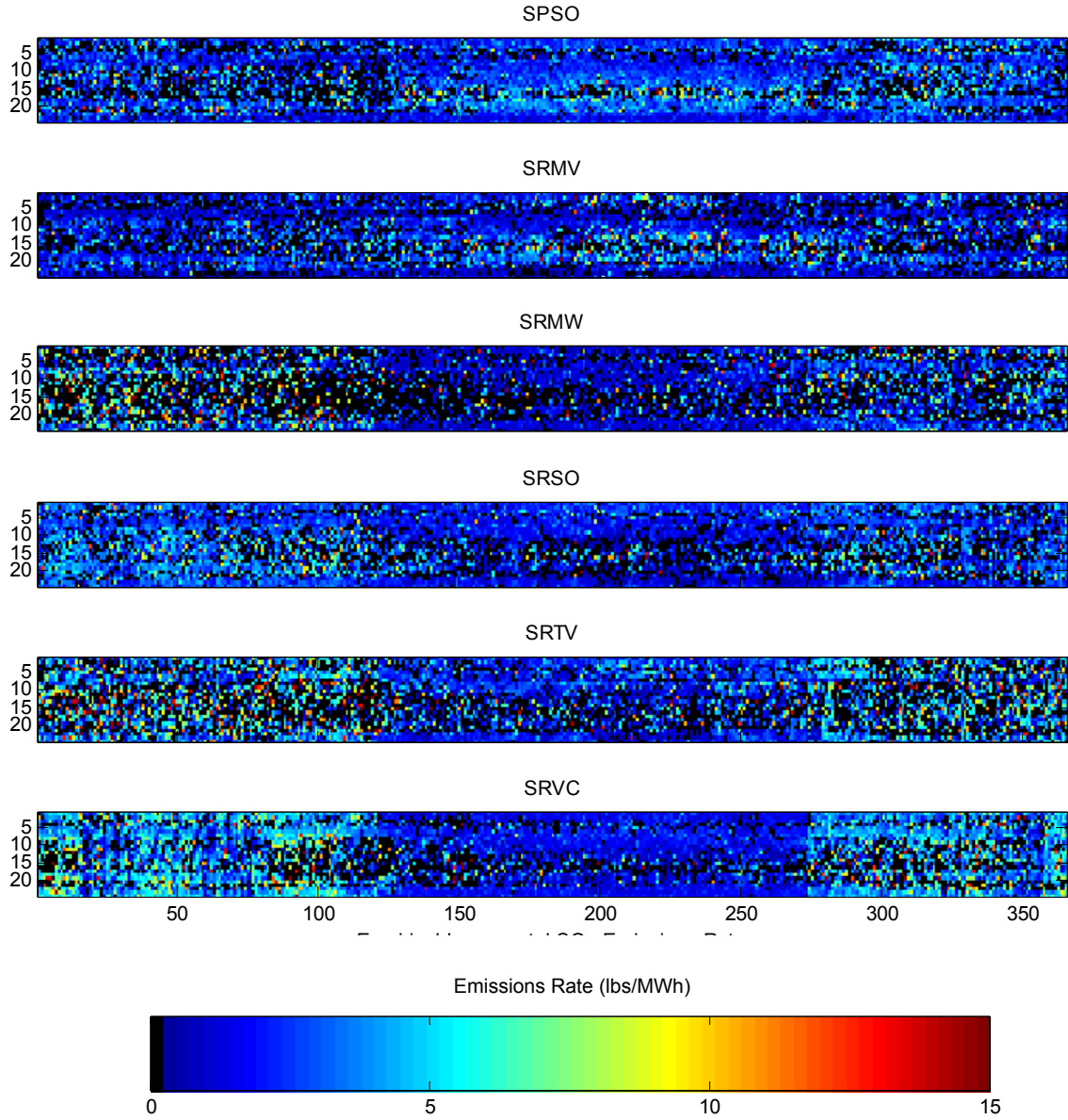
D-10: Empirical Incremental SO₂ Emissions Rate (pounds per MWh)



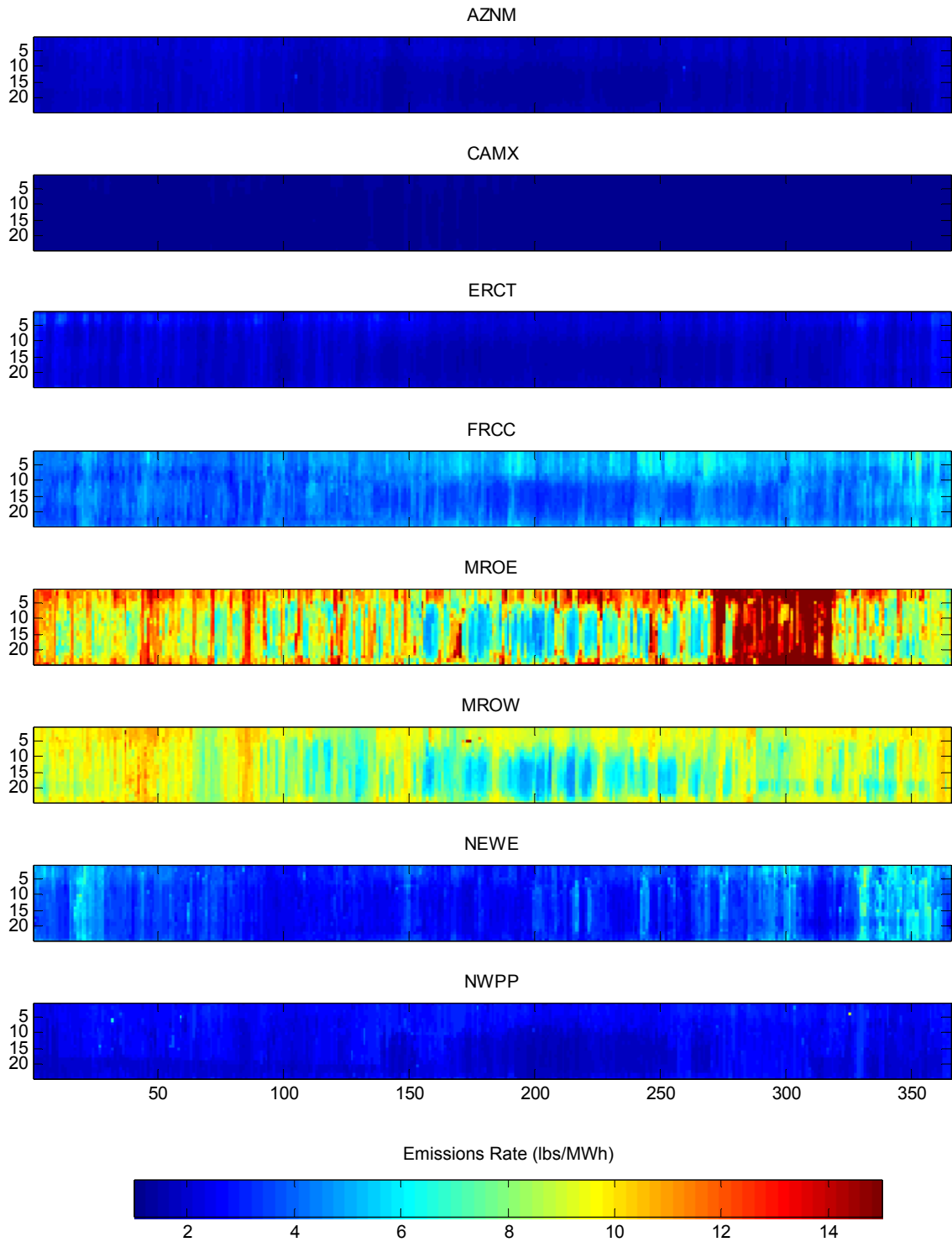
D-10 (continued): Empirical Incremental SO₂ Emissions Rate



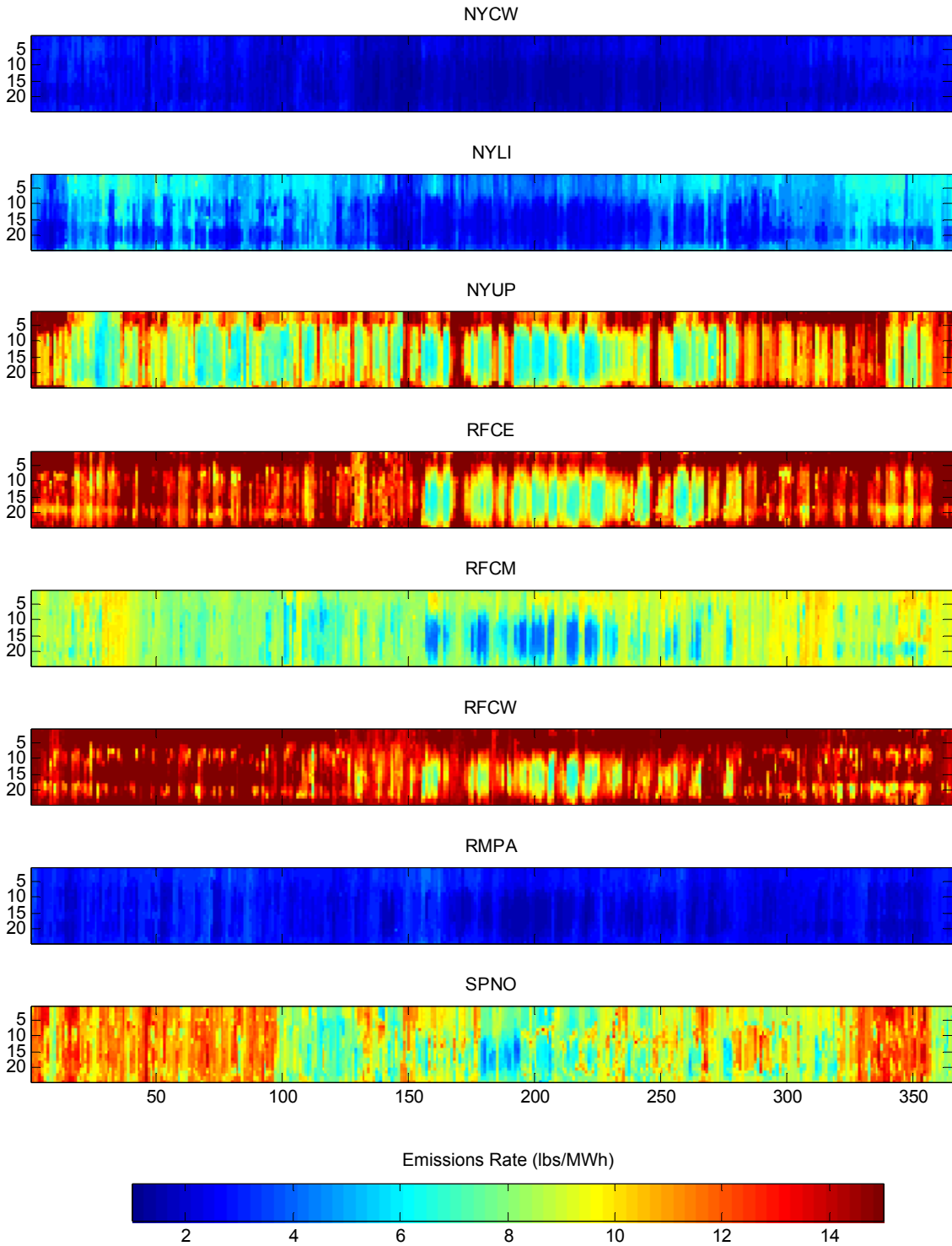
D-10 (continued): Empirical Incremental SO₂ Emissions Rate



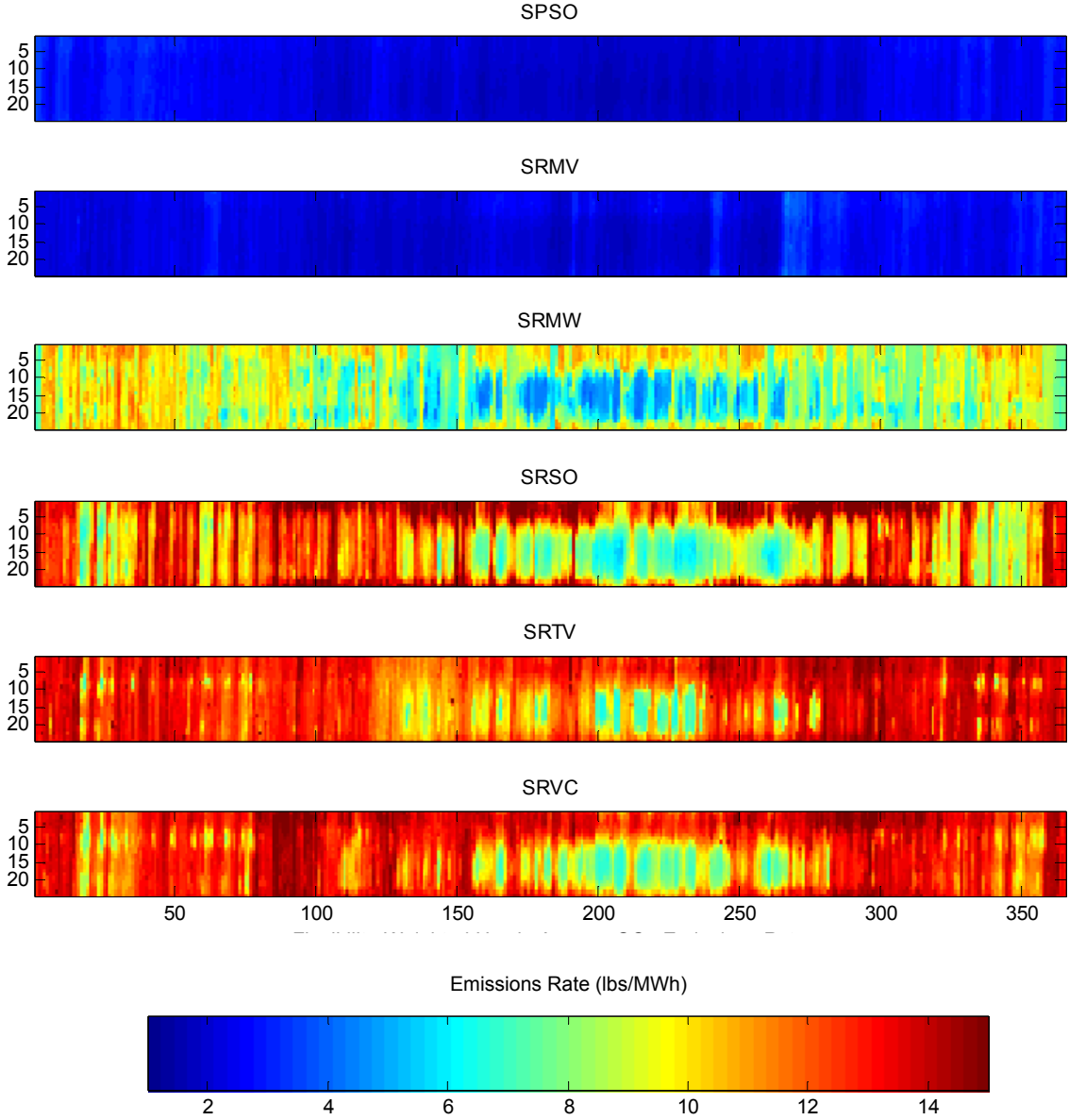
D-11: Flexibility-Weighted Hourly Average SO₂ Emissions Rate (pounds per MWh)



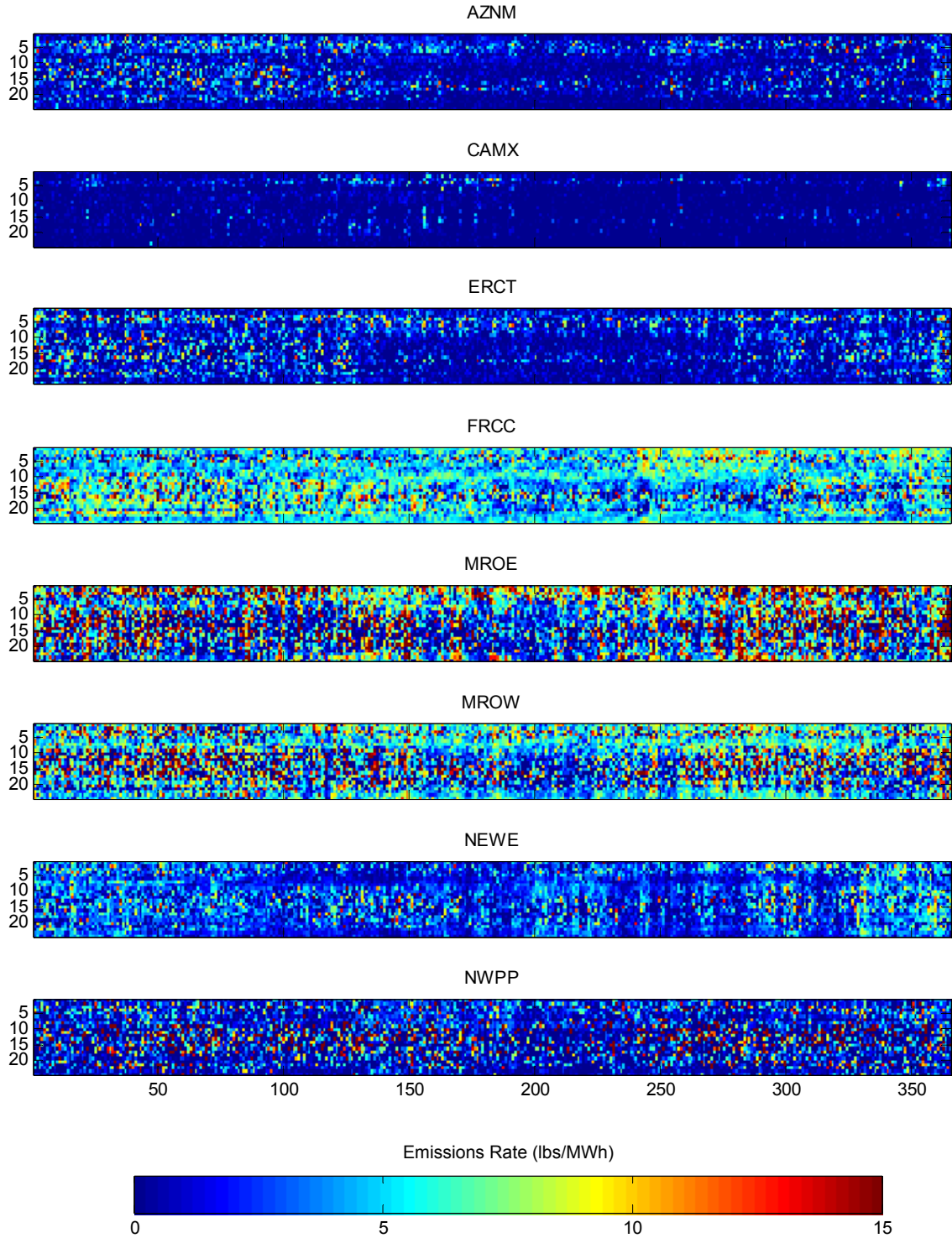
D-11 (continued): Flexibility-Weighted Hourly Average SO₂ Emissions Rate



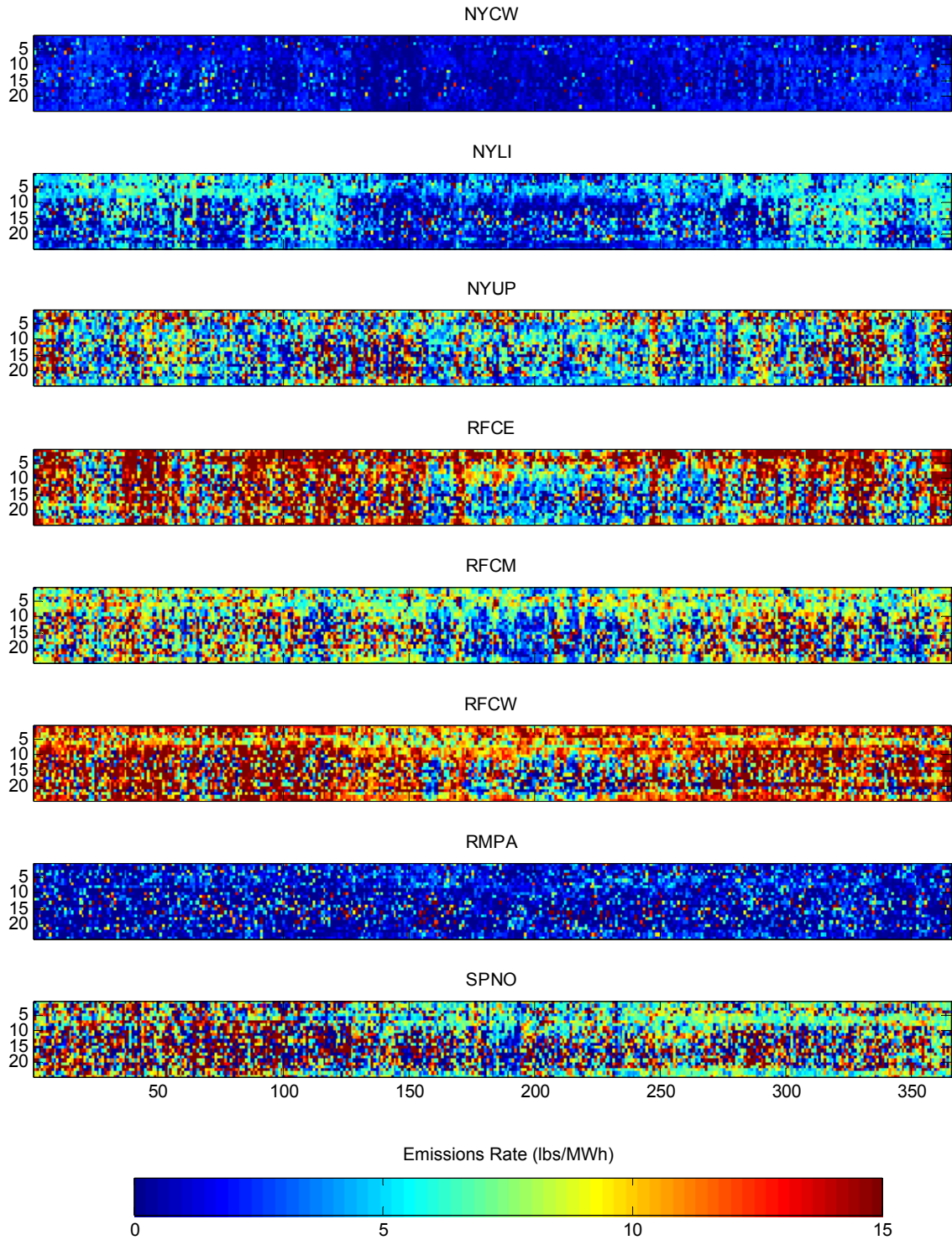
D-11 (continued): Flexibility-Weighted Hourly Average SO₂ Emissions Rate



D-12: Load-Following Incremental SO₂ Emissions Rate (pounds per MWh)



D-12 (continued): Load-Following Incremental SO₂ Emissions Rate



D-12 (continued): Load-Following Incremental SO₂ Emissions Rate

