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The North American Electric Grid as an Exchange Network: An Approach for Evaluating Energy Resource Composition and Greenhouse Gas Mitigation

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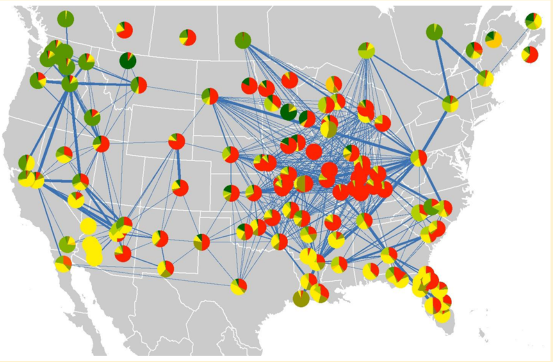
Supporting Information

ABSTRACT: Using a complex network framework, the North American electric grid is modeled as a dynamic, equilibrium-based supply chain of more than 100 interconnected power control areas (PCAs) in the contiguous United States, Canada, and Northern Mexico. Monthly generation and yearly inter-PCA exchange data reported by PCAs are used to estimate a directed network topology. Variables including electricity, as well as primary fuels, technologies, and greenhouse gas emissions associated with power generation can be traced through the network, providing energy source composition statistics for power consumers at a given location. Results show opportunities for more precise measurement by consumers of emissions occurring on their behalf at power plants. Specifically, we show a larger range of possible factors (~0 to 1.3 kgCO_2/kWh) as compared to the range provided by the EPA's eGRID analysis (~0.4 to 1 kgCO_2/kWh). We also show that 66–73% of the variance in PCA-level estimated emissions savings is the result of PCA-to-PCA differences that are not captured by the larger eGRID subregions. The increased precision could bolster development of effective greenhouse gas reporting and mitigation policies. This study also highlights the need for improvements in the consistency and spatiotemporal resolution of PCA-level generation and exchange data reporting.



INTRODUCTION

From generation to point of consumption, electricity flow is dictated by a combination of physics, policy and financial market economics, both short- and long-term. In practice, disentangling these dynamics is difficult. Hence, it is often impossible to describe a given electron's spatial origin, the type of fuel burned to produce it, or the technology employed to generate it.

Yet, there are reasons motivating a better quantitative understanding of where and from what generative sources electricity originates as well as a sharper picture of the topology that supports electricity flow. In the United States, the responsibility to reduce greenhouse gas emissions according to Environmental Protection Agency (EPA) guidelines rests largely on state-level policymakers. The primary opportunity to do so is through power plants, the nation's largest collective source of emissions.[1] However, the effectiveness of any such power plant emissions mitigation policies cannot be devised clearly or fairly to all stakeholders without an accurate, detailed quantification of what entities are indeed responsible for emissions, both from power production and consumption viewpoints. Consumers of grid power often rely on information provided by utilities or aggregated data from entities like the EPA's Emissions & Generation Resource Integrated Database (eGRID)[2,3] or the U.S. Energy Information Administration (EIA)[4] to assess their electricity fuel and technology generation mix and consequent emissions. Yet, from an electricity consumer perspective, these approaches for quantifying emissions are coarse in terms of space-time resolution and do not take into account electricity exchanges, which comprise approximately 25% of total annual generation. In anticipation of stricter greenhouse gas regulations and eventual carbon pricing, both producers and consumers of electricity need to better understand the dynamics of carbon-heavy fuels in their supply network.[5]

A recent study[6] makes clear the value of differentiating power producer- versus consumer-oriented emissions profiles: climate policies that emphasize energy conservation must account for interregional electricity transfers if they are to have the intended beneficial effects. The study provides the conceptual foundation for tracing greenhouse gas emissions through a virtual network by providing a simple, but compelling example using China. They divide the country into six interconnected

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regions. Each region acts as both a consumer and a producer of electrical energy. By tracing the largescale power flow, the virtual carbon "flow" (i.e., the responsibility for the given emissions) is described. In our study, we extend their framework to North America in an effort to better understand the effects of these significant (~25% of total annual generation) operational exchanges among grid operators. Rather than describing virtual carbon flows, we focus our attention on tracing reported power flow through the electrical grid as a means of logically associating in situ consumption with emissions that may occur elsewhere in the system. We construct a topology for the power generation and exchanges among the authorities that operate the North American grid, based on a combination of reported data.

The perspective offered here differs from the vast breadth of literature that has studied the grid as an interconnected network at the highly detailed infrastructural level[7−10] in two significant ways. First, our approach explicitly does not utilize information about *physical* power flow at the grid infrastructural level (i.e., along specific transmission lines) as others do, although we recognize this as an extremely important aspect of grid design and engineering. Instead, this study focuses on modeling the reported aggregate power flow among grid operators in an effort to better delineate producer- versus consumer-oriented emissions attribution. And second, our study is not meant to evaluate the reliability and vulnerability of the grid to rapid cascading failures brought about by natural disasters, physical attacks, or operational errors.

There has also been a great deal of work in recent years aimed at estimating hourly marginal emissions factors for the U.S. electric grid,[11] with particular emphasis on the greenhouse gas impacts of widespread adoption of renewable distributed generation[12] and plug-in electric vehicles.[13] Our model uses national energy survey data and a standard spatial taxonomy for tracking electricity generation and exchanges at the level of PCA and PCA equivalents (e.g., Canadian provinces). In doing so, our model distinguishes itself from prior work by accounting for system-wide electricity transfer effects that are necessarily excluded from papers that look only at individual or small groups of states, independent system operators (ISOs), or Regional Transmission Organizations (RTOs); and by providing results at a higher spatial resolution (PCA-level) than other national models. We underscore the significance of spatial heterogeneity in both marginal and baseload emissions profiles just as others rightly emphasize the significance of temporal heterogeneity in these systems.[14]

■ MATERIALS AND METHODS

While algorithmic and other methodological details can be found in the Supporting Information (SI), in summary, the network is constructed using the PCA-level power generation, interchange, and CO_2 emission factors that were publically available in late 2013. A PCA is, according to the EPA's eGRID[3] "a portion of an integrated power grid for which a single dispatcher has operational control of all electric generators." Previous research has mentioned that, despite the importance of doing so, it is difficult to track these exchanges in practice,[2] a key problem we address here. The network methodology borrows its conceptual foundation from the recent study[6] discussed in the introduction section. That framework treats entities as both producers and consumers, tracing responsibility for carbon emissions through the network via energy exchanges. Similarly, we trace electricity, its generative fuel and technology mix, and associated CO_2 emissions through a complex network of exchanges. Each PCA is treated as a node in the network, and is appropriated a temporal statistical profile both as a producer and as a consumer.

The network consists of 120 power control areas (PCAs), several of which are coupled with regions of Canada (13 in total) and Mexico (1) for a total of 134 nodes. For simplicity, we will refer to nodes outside of the United States as PCAs in some cases going forward. PCAs can be composed of single individual municipal utilities (e.g., Seattle City Light) or even large pools of many utilities operating in a market (e.g., PJM Interconnection). Since each PCA has operational control of power dispatch, we collected, organized and cleaned *monthly* electricity generation data from a variety of data sources. For the PCA in Mexico, only yearly aggregated generation data were available. As such, we assumed that for each month its generation profile was identical and summed to the total electricity generated over the year. Since this represents approximately only 0.5% of all electricity generated by all 134 PCAs in total, we expect the effect of this assumption to be small in its influence on network total results (e.g., influence on electricity transfers into the United States from Mexico). Data from EIA's Electric Power Annual (year 2012) contain monthly generation per fuel type for each plant in the United States.[4] Monthly and yearly Canadian power generation data from 2012 come from CANSIM, Statistics Canada's primary socio-economic database.[15] Data on the Mexican power grid originates from Comisión Federal de Electricidad[16] with Supporting Information provided by Carbon Monitoring for Action.[17] These sources capture the fuel generation profile of each PCA. For each PCA, we have for each month: total electricity generated (MWh), total fuel "burned" and technology used to generate that electricity (mmBTU), both from 2012, and total CO_2 emitted from generating the electricity using power plant-level, per-fuel tCO_2/MWh factors from 2009.[18]

PCAs report year-total electricity (MWh) that they bought and sold with one another. Each PCA reports electricity (MWh) delivered to other PCAs (if any) and also electricity received from any other PCAs (if any). Electricity transfer data is obtained from FERC Form 714.[19] These data were collected, organized and cleaned for major discrepancies using a variety of data sources. The SI provides detail on how discrepancies were handled.

Energy consumption associated with transmission losses is implicitly assigned to generating PCAs. All electrical energy that is not transferred out of a PCA, including the excess generation that is necessary to deliver a certain amount of electricity to a neighboring PCA, is counted as "self-consumed" by the PCA. An enhanced approach might assign responsibility for these emissions to intermediate entities along the transmission path, but the present model precludes such an analysis.

We use the *monthly* generation and *yearly* transfer data to infer a directed PCA network, described in detail in the SI. The concept employed is based on recent research on carbon emission flow networks.[6] In summary, the output of the network model allows for treatment of each PCA as a "consumer" by allowing statistical aggregate inference the electricity that is actually available for purchase from any PCA after considering all network transfers. In other words, because of the transfers, what a buyer actually purchases from a utility within a PCA can be effectively generated from a different

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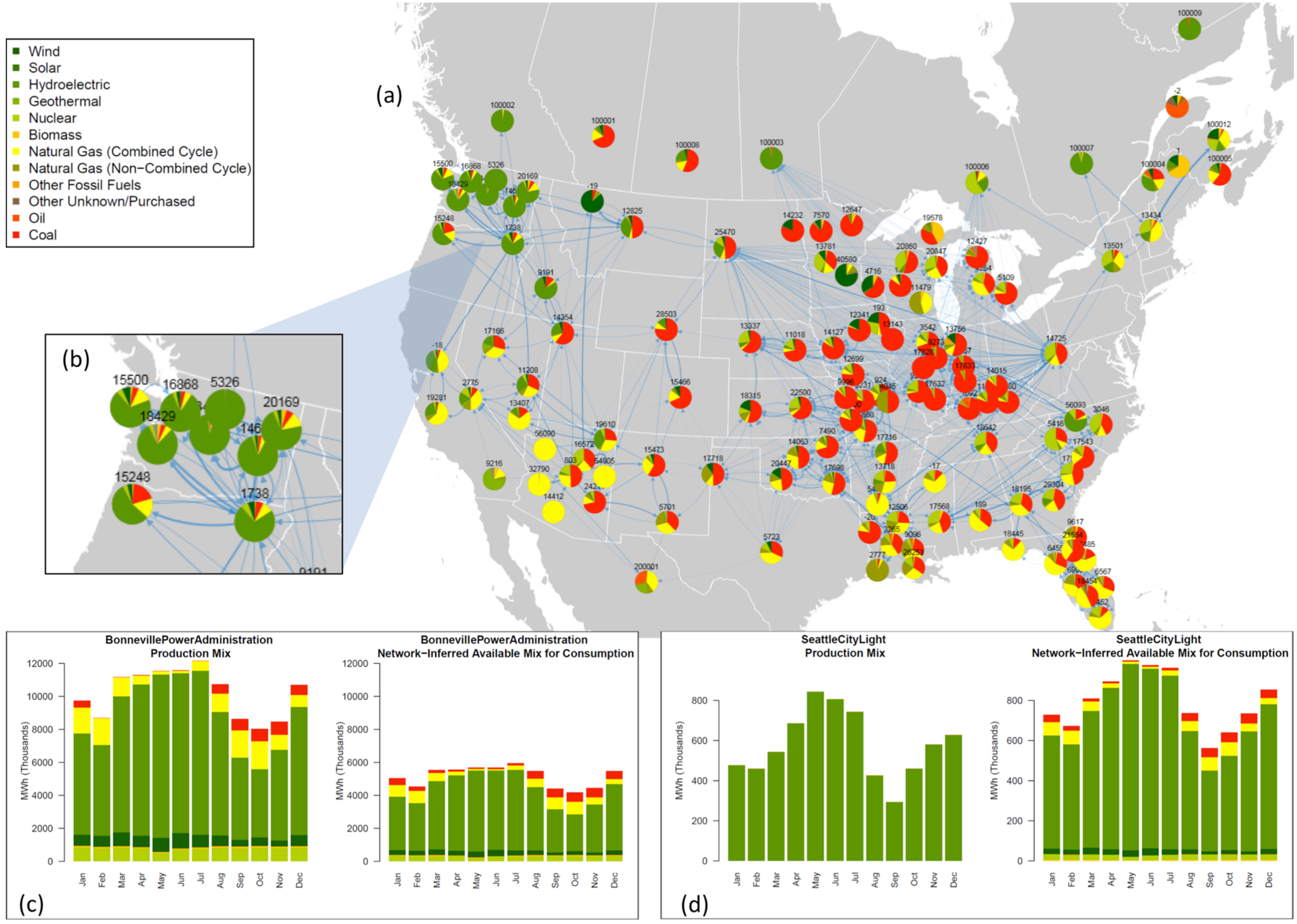

Figure 1. (a) The full PCA network is displayed geographically for aggregated electricity consumption in 2012. Each node represents a PCA and each link a relative transfer from between pairs of PCAs. Nodes are colored proportional to the fuels and technologies comprising the mix in MWh available there after accounting for all transfers. Edge sizes are proportioned to reflect the composition of an incoming transfer relative (from 0 to 100%) to a receiving PCA's total available electricity. Map made using Natural Earth data. (b) The inset panel focuses on the northwestern United States. Nodes are slightly expanded for ease of visualization. (c) The monthly reported electricity production portfolio (left) and monthly network-inferred virtual consumption mix (right) is displayed for Bonneville Power Administration (node number 1738). (d) The same as (c) is displayed but for Seattle City Light (node number 16868).

statistical mix of what was originally produced by the power plants within that PCA. Thus, we can delineate statistical attributes of that mix for any PCA as a "producer" (directly from generation data) or a "consumer" (as inferred by the network model, described next).

To infer the structure of the network, a square matrix X_{NxN}, where $N = 134$, is constructed. An entry X_{ij} is the total amount of electricity in a year that is sent from PCA i to PCA j. In entries X_{ij} where $i = j$, this is the total amount of electricity generated by power plants controlled by PCA i leftover after accounting for all transfers out to neighboring PCAs. Since PCA level power generation data is reported monthly, we wish to estimate properties of the network for each month. Hence we construct $XNORM_{NxN}$, where each row is made to sum to 1. This normalized matrix is used to estimate the flow of monthly electricity generation through the network via an algorithm described in detail in the SI. This algorithm outputs the consumption properties of each PCA, or what purchasers of electricity consume on a statistical monthly average. Detailed assumptions and caveats built into the estimation of $XNORM_{NxN}$ and into the algorithm used to estimate consumption statistics are described in the SI. The network model is constructed such that the sum of electricity, fuels used to generate it, and the associated CO_2 emissions is equivalent when integrating over all PCAs as producers versus as consumers. The distribution of all these resources, however, is significantly different when comparing, in a pairwise fashion, PCAs to themselves as producers and consumers.

RESULTS

Using data summed over all months of 2012, Figure 1(a) illustrates this network graphically across the continental United States along with coupled regions of Canada and Mexico. Figure 1(b) highlights a portion of the network, zooming in on the topology of the northwestern United States as an example. Spatial-temporal redistribution of resources is exemplified in panels (c) and (d) via PCAs (which are, in this case, individual utilities) located in Seattle (Seattle City Light, SCL) and Bonneville Power Administration (BPA), respectively. SCL as a producer generates almost exclusively hydroelectric power. In contrast, the supply network model infers that those who purchase power directly from this utility actually consume a small but significant portion of natural gas and coal-based electricity, as well as much smaller quantities of

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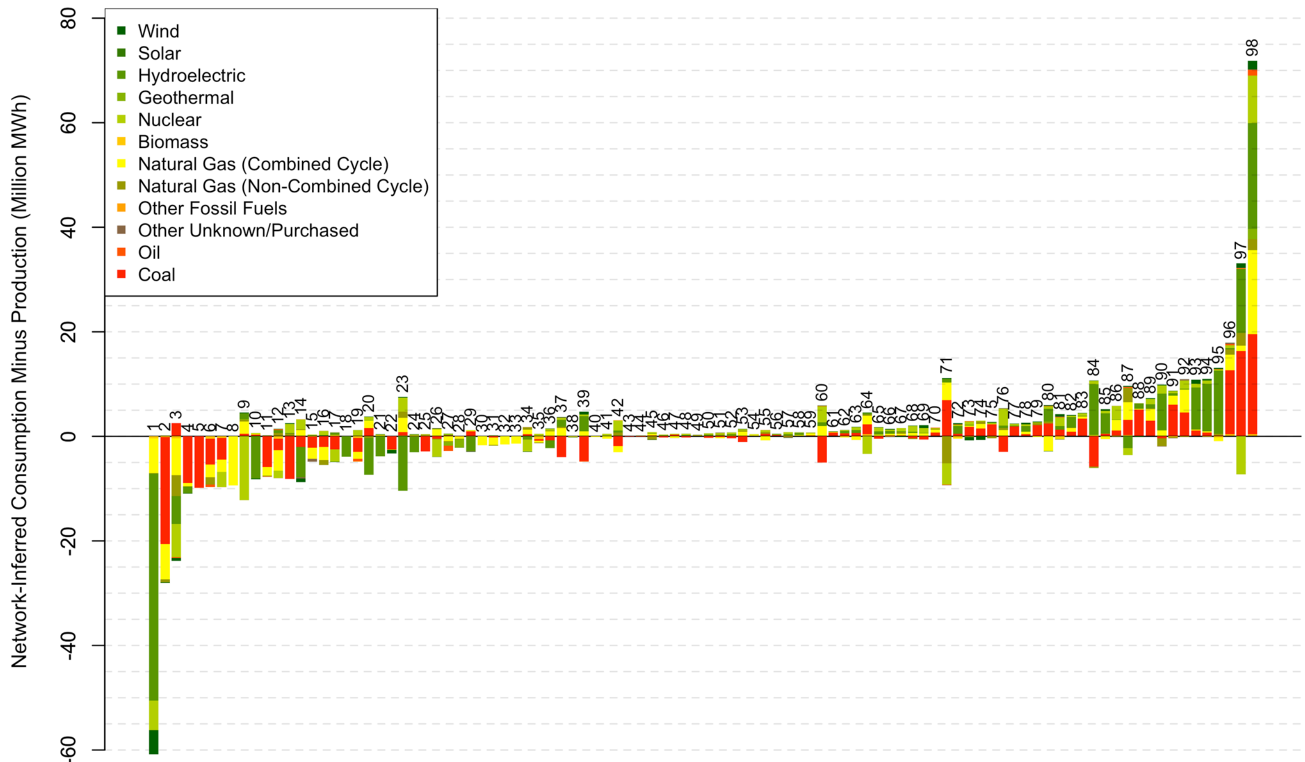

Figure 2. For each PCA that either receives or delivers electricity to any other PCA and is not a "pass through node" (see SI), net network-inferred consumption minus production for each electricity-generating resource is shown in millions of MWh total for 2012. For any PCA, a resource falling below 0 is interpreted as a net exported resource (note: importantly, that this does not mean that customers of the PCA did not consume any electricity from that particular resource, but rather, in net the PCA generated more than it consumed). Similarly, an electricity resource falling above 0 is interpreted as net imported. The integral of all resources over all PCAs above the 0 line (~373 million MWh) is approximately equal to the integral of all resources over all PCAs below the 0 line (~363 million MWh), a reflection of the conservation of resources preserved by the network model. (The inequality is a result of the behavior of pass-through nodes; see SI). PCAs are sorted by total electricity imported (which can be negative when exports exceeds imports), ascending from left to right. Number codes above each stacked bar correspond to a PCA's rank by total net imported electricity in ascending order; these can be found in SI: Table S1.

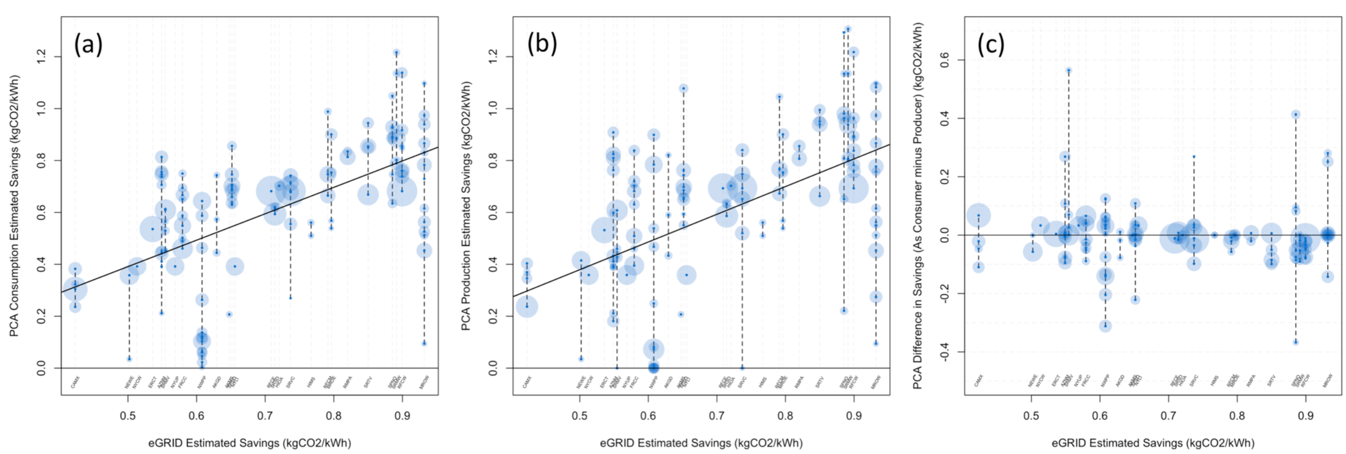

Figure 3. (a) When treating each PCA as a consumer, as inferred by the network model, $kgCO_2$ saved per kWh of electricity offset (e.g., achieved via energy efficiency initiatives or off-grid distributed generation installation choices) is displayed for each PCA (vertical axis) against the same but for the EPA's eGRID subregion in which it resides (horizontal axis). Dashed black vertical lines (light gray when outside the range of PCAs) serve to visually associate PCAs with corresponding eGRID subregions, acronyms of which are displayed at an angle near the horizontal axis. Each blue dot represents an individual PCA and the semitransparent blue circle surrounding it is sized proportional to the 2012 total network-inferred electricity available for consumption, after all transfers. The solid black line represents a linear regression fit to these two fields, with an $R^2 = 0.34$. (b) The same as panel (a) but while treating each PCA as a producer. The linear regression fit has an $R^2 = 0.27$. (c) To illustrate the difference in inferred achievable $kgCO_2$/kWh savings between treating a PCA as a consumer versus a producer, *y*-axis values from panel (a) are subtracted from those in panel (a) and plotted along with corresponding eGRID estimates.

electricity derived from other resources. SCL can be viewed as a net importer of electricity since it consumes more electricity than it generates over the course of the year. SCL is a consumer of coal (~3% annual average) and natural gas (~6% annual

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average) based electricity, as inferred by the network using 2012 data. This consumption is highest (~8% for coal and ~12% for natural gas) during September when less hydroelectric power is generated on the whole in the northwestern United States. In contrast, BPA is a net exporter of power, particularly at the peak of the spring and early summer hydrological season.

In both cases, we note that these are statistical aggregate monthly features and do not reflect in either case the daily, hourly, or minute by minute variations of power production and consumption. This is a topic that deserves attention in future research but is currently constrained by lack of data availability; specifically, transfers are almost exclusively available at an annual total aggregate scale. This topic is discussed more in Materials and Methods.

Figure 2 more comprehensively characterizes the net statistics of production versus inferred consumption. Specifically, Figure 2 synthesizes importer-versus-exporter statistics for all PCAs who exchange electricity with at least one other PCA and who do not act as "pass through nodes" (which represents the majority of PCAs, 73% or 98 out of 134, where 107 exchange electricity but only 98 do not act as "pass through" nodes; see SI for more detail). In Figure 2, PCAs are represented as either net "importer" (a PCA that receives more electricity from neighboring PCAs than it generated on its own) or "exporter" (a PCA that generated more electricity than it actually consumes, having delivered a portion to neighboring PCAs) for each type of electricity. A PCA can, for example, be a net exporter of electricity generated from nuclear and single cycle natural gas-based power but a net importer of coal-based electricity (e.g., see bar 71, representing Entergy). Figure 2 summarizes an advance in spatial fidelity of electricity transactions but also falls in line with limited documentation of well understood aggregate-scale North American electricity flow;[20] this could be considered a first-order form of empirical validation. For example, New York ISO and California ISO (bars 97 and 98 respectively in Figure 2) are found to be net importers of electricity. Further validation at a more granular spatial scale is achieved and discussed in a later section (see Figure 3).

Note that Figure 2 does not represent directly the magnitude of each PCA's responsibility as a producer or consumer but serves to concisely highlight the role of the supply network in describing *net* reallocation of resources. The results suggest that each PCA can at once be treated as a producer and a consumer, but that the treatment for each role should sometimes differ substantially. This could, for example, carry implications for respective supply side (producer) versus demand side (consumer) greenhouse gas regulatory policy[6,21,22] and for purchasers who have, to date, only had visibility into what their utility or PCA generates.

Figure 3 highlights the increase in spatial precision achieved by the model, framed in the context of CO_2 emissions that could be reduced through supply or demand side initiatives. This analysis in Figure 3 only considers nonbaseload power plants (see Materials and Methods). The assumption is that when demand is reduced by, for example, one kWh, that reduced demand would result in an equivalent average decrease of deployment of nonbaseload ("marginal") power sources.[3] To illustrate simply, if there is only one nonbaseload plant emitting 0.45 $kgCO_2$/kWh generated, then each kWh of demand reduction via any means would save 0.45 kg of CO_2 emissions.

Following this, in Figure 3(b), we compare $kgCO_2$/kWh emitted by PCAs, when examining the electricity fuel generation profile of each, to the same estimated by corresponding EPA eGRID subregion emission factors. Figure 3(a) does the same but treats each PCA as a consumer, as inferred using the network model. Figure 3(a,b) shows aggregate directional correspondence with eGRID estimates of $kgCO_2$/kWh that can be saved, providing one form of validation for both the producer-consumer perspectives. Figure 3(a) is not drastically different from (b) and as such provides additional credibility for the network approach, since we would not necessarily expect transfers to fundamentally shift the energy landscape. However, Figure 3(c) shows that, for example, in quantifying achievable CO_2 savings, transfers are still important to take into account: treating a PCA as a producer (by assessing statistical attributes of the power it produced) versus as a consumer (by assessing the statistics of the electricity actually consumed by customers of the PCA, after accounting for network transfers) can sometimes result in significant differences of more than ~0.1 and up to ~0.5 $kgCO_2$/kWh.

From Figure 3(a,b), the biggest takeaway concerns variability. While eGRID estimates range between ~0.4 to 1 $kgCO_2$/kWh, the PCAs (*y*-axes) range from ~0 to 1.3 $kgCO_2$/kWh. Notably, PCAs within the NWPP and MROW subregions (~0 to 0.65 and 0.1 to 1.1, respectively) span ranges wider than the range of all eGRID subregions (~0.4 to 1 $kgCO_2$/kWh). Linear regression fits in Figures 3(a,b) have $R2$ values of 0.34 and 0.27, respectively. This can be interpreted to mean that approximately 27−34% of the variance in PCA-level savings is captured by eGRID subregions. The remaining variance resides in PCA-to-PCA differences that are not captured by these larger subregions. Further, even the differences between treating PCAs as producers versus consumers results in ranges of achievable savings per subregion that are often large (e.g., AZNM, NWPP, and SPNO) relative to the entire eGRID range.

Additional characteristics of the PCA network, including those common in network science literature,[23] are captured in the SI. Figure S1 shows the degree distribution of the PCAs, serving to illustrate the network's connection structure. Table S2 captures other common aggregate network statistics, including the average degree, best-fit degree distribution, network-average clustering coefficient, and average shortest path length.[23] The detailed implications of these statistics are discussed in the SI. Figure S2 displays the distribution of proportional electricity that PCAs receive in total from upstream in the network over the course of 2012.

Finally, we test one aspect of the robustness of the insights that emerge from the network model via an uncertainty analysis. While the details on our approach can be found in Materials and Methods, we test the sensitivity of the insights to discrepancies among PCA self-reported transactions that are difficult to resolve. Fundamental insights, namely those found in Figures 1−3, are found to be statistically robust. Figure S3 is an alternate version of Figure 2; results therein show that the rank order of net electricity exporting and importing is largely preserved. Figure S4 further quantifies the robustness of importing and exporting insights but at a more granular scale. Figure S5 finds strong robustness in the insights found from Figure 3, adding confidence to the utility for the network model in generating actionable insights for regulatory policy.

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DISCUSSION

This study presents a network-science based framework for modeling the operational-level exchange behavior of the North American electric grid at a monthly time scale for 2012. Specifically, we estimate a topology of how generated electricity flows among operational authorities (PCAs) using self-reported generation and transaction data. Emergent insights include a new ability to characterize rich behavior of any given PCA treated as both a producer and consumer of electricity; the network can be used to infer significant differentials in that treatment. The model allows quantification of space-time statistical aggregate use of fuels, technologies, and associated greenhouse gas emissions, for electricity generation, viewed from either a producer or consumer perspective. While this study has demonstrated this ability with CO_2, it is also possible to infer consumer-perspective statistics including CO_2-equivalent, methane, nitrous oxide emissions, particulates, and other pollutants using this network model.[3]

For one application, this opens the possibility for enhancing the development of supply or demand side (i.e., producer or consumer, respectively) regulatory policy, at a higher spatial and temporal precision than the annual subregion data used currently.[3] This may be especially important given the stated urgency of fossil fuel reduction,[24] and the fact that many initiatives occur at the state level[1] whereas the current state of practice is generally at a coarser-than-state resolution.[3]

A major goal of this and other models is to provide relevant insight about the impacts of humanity's consumptive choices as they occur today and in the future. Unfortunately, stationarity is rarely a feature of real networks, especially ones as large and complex as the U.S. electric grid. While the model does offer a clear path to more frequent updates of the widely adopted emission factors provided by EPA's eGRID, further research is required to evaluate the suitability of historical data as a proxy for present grid behavior.

The most significant caveat of the proposed model is in the modeling of subannual scale electricity exchanges. The exchange data are currently almost exclusively reported only in year-aggregate form, with the exception of a handful of large ISOs and RTOs, including PJM, ISO-NE, CAISO, and MISO, which report their statistics independently of EIA and FERC filings. Many smaller PCAs do no independent reporting and in fact have almost no clear public presence of any kind (e.g., a website). One interesting exception is Bonneville Power Administration, which reports net transfers at 5 min intervals;[25] even this data, however, does not allow us to disentangle which PCAs it is receiving electricty from or sending electricity to. Very recently, the EIA was approved to require high resolution reporting of interchange data by balancing authorities, which is a promising step forward.[26] Indeed, if exchange reporting were extended to at least monthly resolution, confidence in monthly network inferences on consumption could be further validated. Materials and Methods as well as the SI describe our current monthly transfer assumptions made in the absence of subannual scale transfer data.

There is also a need for improvements in data reporting consistency. Several large discrepancies and errors exist in public data sets; in these cases, obvious solutions presented themselves and the errors were corrected. Yet, in some cases, there were no obvious opportunities for error and discrepancy correction, which in turn led to a need for the data uncertainty analysis (SI: Figures S3–S5). In total, of approximately 660 million MWh of discrepancies among self-reported electricity transfer data, approximately 600 million MWh were reparable and the residual 60 million were utilized for estimating uncertainty in core insights. Main findings are robust to these residual transfer uncertainties.

Promoting consistency in the self-reported data given by PCAs could reduce this uncertainty significantly. Specifically, it could be ensured through a simple quality control process that when a PCA x reports a sum of electricity (in MWh) delivered to PCA y over the course of a year, this number matches (or at least that the differences are negligibly small) the sum that PCA y claims to have received from PCA x. The benefits of implementing such a procedure could reduce all input data-related uncertainty in key insights, for example realizable $kgCO_2$/kWh savings (see Figure 3) that could be obtained by implementing energy efficiency measures or distributed generation projects on the demand side.

ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.est.5b03015.

> Computational description of PCA supply network construction methodology, including treatment of "pass-through" PCAs, Summary of network statistical analysis with supporting figures and table, uncertainty characterization and robustness tests, and detailed naming of PCAs in table form with ranks (PDF)

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Notes

The authors declare the following competing financial interest(s): risQ and Lux Research Inc. are each privately held companies.

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REFERENCES

(1) Grant, D.; Bergstrand, K.; Running, K. Effectiveness of US state policies in reducing CO2 emissions from power plants. *Nat. Clim. Change* **2014**, *4* (11), 977–982.

(2) Weber, C. L.; Jaramillo, P.; Marriott, J.; Samaras, C. Uncertainty and variability in accounting for grid electricity in life cycle assessment.

In *IEEE International Symposium on Sustainable Systems and Technology, 2009. ISSST'09.* ; IEEE, 2009; pp 1−8.
(3) DiemA.QuirozC.*How to use eGRID for Carbon Footprinting Electricity Purchases in Greenhouse Gas Emission Inventories*, 2012.
(4) U.S. Energy Information Administration. *Electric Power Annual 2012*; U.S. Energy Information Administration, 2013.
(5) Fan, L.; Hobbs, B. F.; Norman, C. S. Risk aversion and CO_2 regulatory uncertainty in power generation investment: Policy and modeling implications. *J. Environ. Econ. Manag.* **2010**, *60* (3), 193−208.
(6) Kang, C.; Zhou, T.; Chen, Q.; Xu, Q.; Xia, Q.; Ji, Z. Carbon emission flow in networks. *Sci. Rep.* **2012**, *2*, 1−7.
(7) Albert, R.; Albert, I.; Nakarado, G. L. Structural vulnerability of the North American power grid. *Phys. Rev. E* **2004**, *69* (2), 025103.
(8) Chassin, D. P.; Posse, C. Evaluating North American electric grid reliability using the Barabási−Albert network model. *Phys. A* **2005**, *355* (2), 667−677.
(9) Bao, Z. J.; Cao, Y. J.; Wang, G. Z.; Ding, L. J. Analysis of cascading failure in electric grid based on power flow entropy. *Phys. Lett. A* **2009**, *373* (34), 3032−3040.
(10) Bernstein, A.; Bienstock, D.; Hay, D.; Uzunoglu, M.; Zussman, G. *Power Grid Vulnerability to Geographically Correlated Failures-Analysis and Control Implications*, ArXiv Prepr. ArXiv12061099, 2012.
(11) Siler-Evans, K.; Azevedo, I. L.; Morgan, M. G. Marginal emissions factors for the US electricity system. *Environ. Sci. Technol.* **2012**, *46* (9), 4742−4748.
(12) Zhai, P.; Larsen, P.; Millstein, D.; Menon, S.; Masanet, E. The potential for avoided emissions from photovoltaic electricity in the United States. *Energy* **2012**, *47* (1), 443−450.
(13) Sohnen, J.; Fan, Y.; Ogden, J.; Yang, C. A network-based dispatch model for evaluating the spatial and temporal effects of plug-in electric vehicle charging on GHG emissions. *Transp. Res. Part Transp. Environ.* **2015**, *38*, 80−93.
(14) Zivin, J. S. G.; Kotchen, M. J.; Mansur, E. T. Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies. *J. Econ. Behav. Organ.* **2014**, *107*, 248−268.
(15) Statistics Canada. CANSIM - 127−0002 - Electric power generation, by class of electricity producer. http://www5.statcan.gc.ca/cansim/a26?lang=eng&retrLang=eng&id=1270002&tabMode=dataTable&srchLan=-1&p1=-1&p2=9 (accessed December 15, 2014).
(16) Comisión Federal de Electricidad. Datos Técnicos de las Principales Centrales en Operación en 2013. http://egob2.energia.gob.mx/portal/electricidad.html (accessed December 15, 2014).
(17) Ummel, K. *CARMA revisited: an Updated Database of Carbon Dioxide Emissions from Power Plants Worldwide*; Center for Global Development, 2012.
(18) U.S. Environmental Protection Agency. *Emissions & Generation Resource Integrated Database (eGRID) - Eighth edition with year 2009 data (eGRID2012 Version 1.0)*. 2012.
(19) Federal Energy Regulatory Commission. FERC: Documents & Filing - Forms - Form 714 - Annual Electric Balancing Authority Area and Planning Area Report - Data Downloads http://www.ferc.gov/docs-filing/forms/form-714/data.asp (accessed December 15, 2014).
(20) U.S. Energy Information Administration. *Electricity tends to flow south in North America*. 2011.
(21) Wiedmann, T.; Lenzen, M.; Turner, K.; Barrett, J. Examining the global environmental impact of regional consumption activities—Part 2: Review of input−output models for the assessment of environmental impacts embodied in trade. *Ecol. Econ.* **2007**, *61* (1), 15−26.
(22) Wiedmann, T. A review of recent multi-region input−output models used for consumption-based emission and resource accounting. *Ecol. Econ.* **2009**, *69* (2), 211−222.
(23) Albert, R.; Barabási, A.-L. Statistical mechanics of complex networks. *Rev. Mod. Phys.* **2002**, *74* (1), 47.
(24) Allen, M. R.; Barros, V. R.; Broome, J.; Cramer, W.; Christ, R.; Church, J. A.; Clarke, L.; Dahe, Q.; Dasgupta, P.; Dubash, N. K.; et al. *IPCC Fifth Assessment Synthesis Report-Climate Change 2014 Synthesis Report.* 2014.
(25) WIND GENERATION & Total Load in The BPA Balancing Authority. http://transmission.bpa.gov/business/operations/wind/.
(26) Booth, W. *EIA Clearinghouse of Hourly Electric Power Operating Data in 2015*, 2014.

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