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Air pollution co-benefits from strengthening electric transmission and distribution systems

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ABSTRACT

Inefficiencies in the transmission and distribution (T&D) of electricity between suppliers and customers can lead to higher compensatory electricity generation and unanticipated air pollution. Using both life cycle assessments and uncertainty analyses, we estimate the compensatory air pollutants – CO_{2eq}, SO_x, NO_x, and $PM_{2.5}$ – associated with aggregate and non-technical T&D losses at national and subnational scales. Our global analysis estimates that 1 Gigatonne of CO_{2eq} and 1.3 Megatonnes (Mt) NO_x, 1.6 Mt SO_x, and 2 Mt $PM_{2.5}$ are associated with annual aggregate T&D losses. We also find that approximately 274 Mt CO_{2eq}, 367 kilotonnes (kt) NO_x, 486 kt SO_x, and 535 kt $PM_{2.5}$ are emitted due to non-technical T&D losses. Our subnational analysis in the United States demonstrates the variation of emissions savings across regulatory jurisdictions. We present an initial deployment cost analysis for CO_{2eq} reduction which compares deploying smart meters (i.e., reducing non-technical T&D losses) to renewable energy generation expansion. Investments in T&D infrastructure are beneficial in a completely decarbonized system because improvements in the T&D grid can make investments in renewable energy more cost-effective.

1. Introduction

Globally, 10.2 million premature annual deaths, can be attributed to fossil-fuel generation and associated $PM_{2.5}$ emissions [1], a large part of which comes from the electricity sector. There are three main opportunities for emission-saving interventions in the electricity system (i.e., generation, delivery, and consumption), but one of these components (delivery) has often been overlooked leaving potential air pollution reductions on the table. In their submitted Nationally Determined Contributions (NDCs) in 2015, 110 countries mentioned renewable energy targets, while only 32 countries mentioned grid efficiency in their climate mitigation strategies [2]. Our analysis unveils the link between grid inefficiencies and air pollution at global, national, and sub-national scales. In 2018, energy-related CO_{2eq} emissions reached a historic high of 33.1 Gigatonnes of carbon dioxide (Gt CO_{2eq}) globally [3]. To improve environmental sustainability and decarbonize the electric grid, countries are increasingly focused on shifting generation infrastructure [4–8]. Several analyses evaluate the emissions resulting from current fossil-fuel plants living beyond their historical lifetimes [9–12]. However, policymakers and analysts place little focus on how these emissions are tied to inefficiencies in the delivery of electricity, i.e., in the losses incurred during the transmission and distribution (T&D) of electricity. Reducing T&D losses can be an important climate abatement strategy that will lead to less generation infrastructure investments, reduce fossil-fuel operational needs, and leverage energy efficiency [2,13].

T&D infrastructure is the primary means of delivering electricity from the power plant to the end-user. Here we define T&D losses as the percentage of electricity that is lost between electricity generation at the power plant, and the final amount delivered to the consumer. T&D losses mean that electric utilities must generate more than 1 kW-hour (kWh) to deliver 1 kWh to the consumer. We refer to compensatory generation as that required to make up for T&D losses. These losses primarily result from T&D inefficiencies that can be technical (e.g., physical constraints and heat loss), or non-technical (e.g., theft, fraud,

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defective meters, or billing issues). We estimate that, globally, 2100 TWh of compensatory generation per year is associated with T&D losses (based on 2017 data). In 2017, aggregate losses – technical and non-technical combined – were approximately 58% in Haiti, 22% in Ghana, 18% in India, 5% in the USA, and 1% in Singapore [2].

Meanwhile, non-technical losses can make up to 77% of the aggregate losses. For example, non-technical losses were approximately 45% in Haiti, 11% in Ghana, 6% in India, and 1.3% in the USA [2]. These high delivery losses combined with the fact that over 65 countries source 60% or more of their electricity from fossil-fuels (Supplementary Information Fig. S2), leads to 1100 Mt CO_{2eq}, 0.93 Mt SO_x, 0.91 Mt NO_x, 0.19 Mt $PM_{2.5}$ annually. In addition to the benefits of reducing co-pollutants, improving T&D efficiency reinforces benefits for renewable energy, which often require higher initial generation investments than their fossil-fuel counterparts [14]. As nations retire fossil-fuel generators [15], grid efficiency will reduce renewable and nonrenewable investment needs and ensure that more low carbon energy reaches its intended consumers [16,17].

T&D efficiency improvements can result from reducing technical losses directly or from changes in demand through reducing non-technical losses [2]. Technical losses can be reduced by deploying high-voltage transmission lines, while non-technical loss reductions can occur through reduction in electricity theft, deployment of smart meters, and greater accountability in bill paying. Some studies suggest that reducing non-technical losses could reduce the associated electricity consumption by 33%–50% [2,18]. In the USA, it is estimated that smart meters can reduce overall electricity consumption by 6% [19]. In 2018 in the USA, there was 56% adoption of smart meters, and by 2020, there was around 75% adoption [20,21]. The resulting reduction in air pollution necessitates granular sub-national analyses that identify hotspots of high T&D losses and grid inefficiencies that are large contributors to compensatory generation and associated air pollution.

We address these questions on T&D inefficiencies with three key contributions. Our first contribution is to quantify air pollution emissions associated with T&D losses in 142 countries and determine how much they can be reduced. A previous study determined that 1 Gt CO_{2eq} per year are released due to T&D losses and approximately half can be mitigated [2], but the co-benefits of reduced air pollution (SO_x, NO_x, or $PM_{2.5}$ emissions) were not estimated [2,22–24]. Considering co-pollutants is vital due to their linkages with premature deaths and births [1,25–27]. Emissions estimates using life cycle assessments (LCAs) often concentrate on the functional unit of electricity generated at the source [28–31]. This choice means that the resulting emissions factor misses the compensatory generation that results from T&D losses in the delivery of electricity. Our analysis first expands upon the more common functional unit of 1 kilowatt hour (kWh) generated to include grid inefficiencies by using one kWh delivered.

Second, we argue that examining sub-national scales is crucial for locating opportunities to reduce grid inefficiencies and the related harmful emissions. Other studies do not examine emissions at sub-national scales [2,22–24]. We investigate the level of emissions that could be avoided by reducing aggregate and non-technical T&D losses and associated compensatory generation, within different electric regulatory structures at multinational and two subnational scales of the USA, under three scenarios: business-*as*-usual (BAU) for T&D efficiency, moderate ambition T&D efficiency, and high ambition T&D efficiency. Third, we estimate the initial deployment cost associated with reducing non-technical losses through implementing smart meters, and we compare this value to the initial deployment cost for renewable energy investments (i.e., wind turbines and solar panel deployment). This estimation provides a better understanding of the viability of reducing air pollution emissions from non-technical losses.

2. Methods

2.1. Transmission and distribution losses

In our analysis, we calculate the total T&D losses (n_{TD}) associated with each generation source for a given region, by taking the reported transmission and distribution losses (U_{TDloss}, in TWh) in the country and dividing this number by the total generation within the country (equation (1)). The generation associated with T&D losses ($U_{TD,g}$, in TWh) from power plant g, is determined by multiplying the percentage of the reported T&D losses in the region (n_{TD}) by the energy contribution ($U_{gen,g}$, in TWh) from that electricity source (equation (2)). In our analyses, the reported T&D losses in the region can be for aggregate losses or non-technical losses.

$$n_{TD} = \frac{U_{TDloss}}{\sum_{g \in G} U_{gen,g}} \tag{1}$$

$$U_{TD} = \sum_{g \in G} U_{TD,g} = \sum_{g \in G} n_{TD} U_{gen,g} \tag{2}$$

The electricity generation for each region ($U_{gen,g}$, in TWh) is sourced from the IEA's Electricity Information Statistics [32]. Aggregate T&D losses (n_{TD}) vary across countries, with the lowest at 1.2% in Singapore and the highest at 60% in Haiti. Although there is also a wide variation of losses within a region, for the global analysis we assume uniform T&D losses for individual countries due to a lack of more detailed data for each of the 142 countries. We define region-level aggregate losses as the sum of technical losses (n_{TL}) and non-technical losses (n_{NTL}), as seen in equation (3).

$$n_{TD} = n_{TL} + n_{NTL} \tag{3}$$

Within relatively efficient electricity systems the non-technical losses resulting from theft can be 1–2% [33]. To estimate loss reduction in T&D, we developed two cases related to (1) moderate- and (2) high-efficiency investments. The upper bound of T&D losses corresponds to BAU losses. The lower bound on T&D efficiency represents a high ambition for T&D investments and corresponds to the maximum calculable reduction in aggregate T&D losses, based on the 2% T&D losses observed in Singapore, and some parts of the USA. We assume under the moderate T&D investment scenario each country reduces its losses by 33% [2]. Fig. 1 depicts the system boundary of what we are considering in these scenarios for the transmission and distribution of electricity generation. We exclude consideration of material extraction for and the building of transmission and distribution infrastructure.

2.2. Emissions from transmission and distribution losses

To date, the LCA literature has primarily focused on emissions from electricity generated (E_{gen}, in Megatonnes, Mt) rather than from delivered (E_{del}) [35,36]. Surana and Jordaan [2] attempted to remedy this gap by providing an in-depth analysis of the CO_{2eq} emissions associated with T&D losses in 142 countries. We expand on this work by analyzing the air pollution emissions associated with T&D losses (E_{loss}, in Mt).

Here we define the emissions associated with the transmission and distribution losses of electricity transportation, as seen in equation (4).

$$E_{loss} = \sum EF_g U_{TD,g} k \tag{4}$$

The emissions factor (EF_g, in g/kWh) [37–45] represents the life cycle emissions associated with generating electricity from power plant g. k_i is the adjustment factor for country I, and is used to estimate the proportion of fossil-fuel technologies (i.e. amount of supercritical and subcritical coal) using the reported efficiency in each country. For the full methods for the adjustment calculation, see methods of Sarah and Jordaan [2]. Humperdinck and Nierop [46] was used to update the efficiencies for the select countries and the rest were sourced from the IEA

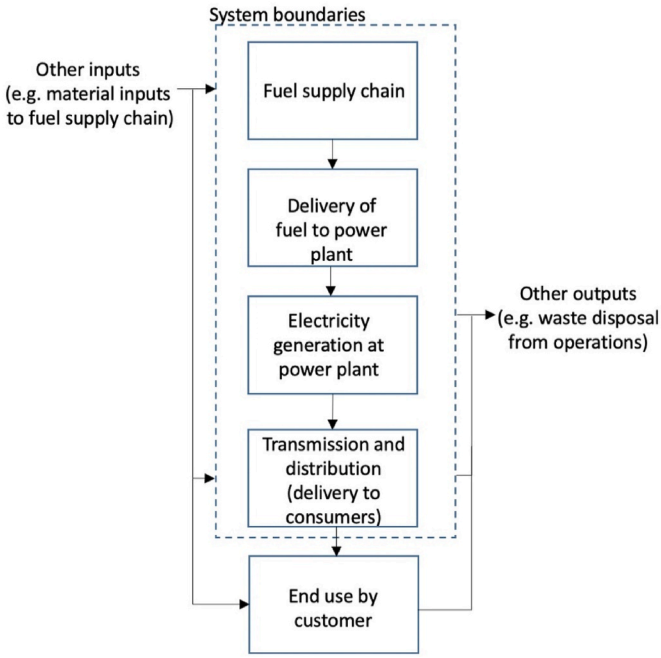

Fig. 1. System boundary for the emissions analysis of the transmission and distribution of electricity. Based on Jordaan et al. [34].

and Surana and Jordaan [2] [32]. To account for the range in efficiencies across reported emissions studies we perform a simple harmonization for combustion plants (i.e. oil, NG, coal, and biomass). The simple harmonization involves scaling the EF by the efficiency ratio (k_g) in equation (5), where η is the reported efficiency for the EF in the literature, and j represents the different sources of information

$$k_g = \frac{\frac{1}{L}\sum_{j=1}^{L}\eta_j}{\eta_j} \tag{5}$$

Coal and natural gas-fired power plants can have two possible technologies. Across countries, the share of subcritical pulverized coal (SubCPC) and supercritical pulverized coal (SCPC) plants varies. We estimated the share of SubCPC and SCPC using the average reported higher heating value efficiency of coal plants within a country. Similar to coal we estimated the share of natural gas combined cycle and natural gas combustion turbine plants within each country. For the estimation of emissions factor for coal and natural gas-fired power plants see Surana and Jordaan [2]. The life cycle emissions factor data and sources can be found in Supplementary Tables S6–S8. The technologies included in this analysis can be found in Supplementary Table S9. We note that the emissions factors of air pollutants will depend on many factors (e.g., fuel types, sulfur content, and end of pipe technology), and it would be valuable to identify how country and regional specific emissions factors vary.

The number of coal plant estimates was calculated using the EPA's Greenhouse Gas Equivalencies calculator [47].

2.3. Uncertainty analysis

There is uncertainty associated with each of the emissions factors. We apply triangular distributions and a Monte Carlo simulation to determine how uncertainty in the emissions factors changes the reported impacts at the country level similar to Surana and Jordaan [2]. The Monte Carlo simulation was run for 10,000 simulations and was implemented using a python model. For each country, we calculated EF_{gen} from a triangular distribution with the minimum, median, and maximum values of life cycle emissions for each technology or fuel source i derived from the larger set of LCA studies. Also, for the moderate and highly efficient scenarios, the target losses were calculated from a normal distribution. The standard deviation was one-tenth of the target losses. This step was taken because one cannot be sure if T&D improvements will work as intended and matches the approach taken by Surana and Jordaan [2].

Tables S6–S10 in the supplementary information detail the assumptions used in our analysis [48–53].

2.4. USA electricity system

The USA is made up of three interconnections (Western, ERCOT, and Eastern). Within these interconnections, reliability regions are responsible for ensuring the security of electricity supply from the generators to the electricity consumers in most of the USA bulk electric electricity systems, while the rest of the country is maintained by utility companies. We group the transmission and distribution losses in each state under the entity that controls the balancing of generation and demand across the transmission and distribution system, according to the geospatial file [54]. Some power plants are in areas that are not clearly defined to be in one reliability region and consequently are not included in the maps. Additionally, the EIA data used does not include the Southwest Power Pool as a reliability region.

Within the USA analysis, we use the reported efficiency of the power plants in the EIA dataset. In some cases, the EIA data reported an efficiency higher than the theoretical maximum. In these cases, the average efficiency for that type of power plant determined from the life cycle analysis review was used for the power plant.

2.5. Solar generation savings

We estimate potential savings in solar generation investment using the PVWatts calculator from the National Renewable Energy Laboratory [55]. We calculate the estimated energy output for a standard 4 kW residential solar panel (see Supplementary Information Table S5). We scale the by the estimated level of compensatory generation reductions, using equation (6).

$$G_s = \frac{4(U_r)}{U_s} \tag{6}$$

Here G_s is the installed capacity of residential solar. U_r is the amount of displaced fossil-fuel generation, resulting from more efficient T&D systems. U_s is the amount of electricity generation from solar that is not needed due to a more efficient T&D system.

2.6. Initial deployment cost for CO_2 reduction analysis

We estimate the total cost of purchasing and installing smart meters (C_{SM}, in $) to reduce energy usage. We assume that a smart meter can reduce overall residential energy demand (i.e., T&D losses, customer demand, and theft) by a percentage r. We assume that r is 6% [19]. First, we calculate the number of smart meters needed (M_{NEED}).

$$M_{NEED} = (1 + p_r) \times \Delta U_{NTL} \times \frac{M_{TOT}}{rU_{res}} \tag{7}$$

Here, ΔU_{NTL} (TWh) is the difference in energy lost from non-technical losses between reduction scenarios. M_{TOT} is the total number of residential meters [21]. U_{res} (TWh) is the energy use of the residential sector in 2018 [56]. p_r is the percent of energy reductions that are due to non-technical losses decreasing. From past installations of smart meters, we believe that the range of p_r is between 2 and 40% [57].

Here, the total cost of implementing smart meters (C_{SM}, in $) is found using the number of smart meters needed and the cost per smart meter (c_{SM}, in $). The cost per smart meter is estimated by considering a range of values based on real implementations of smart meters [58].

$$C_{SM} = c_{SM} M_{NEED} \tag{8}$$

The initial deployment cost for CO_{2eq} reductions of smart meters (A_{SM}, in \$) were calculated using equation (9). The U.S. Energy Information Administration gives the USA average CO_{2eq} emissions per kWh (E_{kWh}) in 2020 to be 0.85 pounds CO_{2eq} per kWh [59].

$$A_{SM} = \frac{c_{SM} M_{TOT}}{r E_{kWh} U_{res}} \tag{9}$$

Using the methodology to find the CO_{2eq} avoided annually by a 2.42 MW wind turbine with a capacity factor of 35% as given by the EPA [47], we find the CO_{2eq} avoided annually (E_A) by a 10.0 MW solar plant with a capacity factor (CF) of 24% [60], as shown in equation (10). The total capacity of solar in the United States in 2018 [60] and the number of solar plants in 2018 is used to find the average capacity of a solar plant (CP) (10.0 MW). The annual CO_{2eq} avoided per MWh solar (E_{sol}) is given by the Environmental Protection Agency to be $6.6{*}10^{-7}$ Mt CO_{2eq} per solar plant annually [61]. We find the CO_{2eq} avoided annually by a 10.0 MW solar plant with a capacity factor of 24% to be 0.0141 Mt CO_{2eq} per solar plant annually.

$$E_{A,solar} = (CF)(CP)E_{sol} \tag{10}$$

We find the number of solar plants or wind turbines (N) with equation (11). ΔE_{loss} is the difference in CO_{2eq} emissions (Mt) from non-technical losses between reduction scenarios (equation (11)).

$$N = \Delta E_{loss} E_A \tag{11}$$

We find the price per solar plant or wind turbine, c, (equation (12)) using the construction price per kW [62] (X, in \$) and the average capacity [60] (Cp).

$$c = \chi(Cp) \tag{12}$$

Then, the total cost (C, in \$) is computed in equation (13) [47].

$$C = cN \tag{13}$$

2.7. Limitations

When we consider T&D at aggregate levels, we ignore the fact that T&D efficiency will vary by line due to the spatial scale of our model. Thus, it may take less effort to improve T&D losses than expected depending on the amount of variation between the lines. Additionally, we assume that reductions in T&D losses will impact the emissions from each power plant by the same proportion. This assumption is due to the data being aggregated at the annual level for either each country at the global level and power plant in the USA. Further studies could attempt to use timed demand data of each power plant to determine how peaker plants would be affected by reductions in compensatory generation.

We do not have data for the losses of the NERC regions, so they are the area-weighted averages of the state losses. The data available for the NERC regions did not include the Southwest Power Pool and did include the Florida Reliability Coordinating Council; however, the geospatial file had the opposite and included an area of unclear jurisdiction. Additionally, we only have data for non-technical losses at the country level, so any state or NERC analyses of non-technical losses are just a percentage of the aggregate losses.

When we use wind and solar generation to explore carbon mitigation options, we do not account for hourly generation variations. When considering smart meters as a carbon mitigation option, we assume from past installations of smart meters that electricity consumption associated with both non-technical losses and smart meters decreases by 2–40% [57].

We also assume that more accurate billing and reducing the use of faulty meters will not increase overall electricity system demand (i.e., sum of T&D losses, customer demand, theft). Additionally, the initial deployment cost estimates do not consider operational costs or savings from adopting the technologies. Further assumptions of the Monte Carlo methods can be found in Table S10.

3. Results and discussion

3.1. Analysis of multinational co-pollutant emissions

Aggregate T&D losses vary widely across the globe with the most efficient system in Singapore at 2% and the most inefficient in Haiti at 60% (Fig. 2). Non-technical T&D losses also vary greatly with the lowest losses at 0% in a few smaller countries (Bahrain, Iceland, Luxembourg, Singapore, and Trinidad and Tobago), and the greatest losses at 45% in Haiti (Fig. 2). The average air pollution emissions from the full life cycle of electricity delivered – including T&D losses – vary widely by country (Supplementary Figs. S1 and S2). Within the of the countries with the 25 highest aggregate losses we find that there is a slight indication of how these losses translate to emissions. We found that 7 of the 25 most CO_{2eq} intense countries, 9 of the 25 most NO_x intense, 13 of the 25 most SO_x intense, and 9 of the 25 most $PM_{2.5}$ intense were also in the top 25 countries for aggregate losses.

Understanding the link between T&D efficiency and air pollution emissions is becoming increasingly urgent because, despite global commitments to decarbonize, several countries are actively building and operating coal plants to fuel near-term growth [25,63,64]. These power plants are detrimental to both climate and public health goals and are often slated in countries will high levels of T&D losses. For example, in 2019 India generated 805 GWh of electricity from coal, which is expected to increase to 1300 GWh by 2030 following the country's 4.5% annual demand growth [65]. The associated $PM_{2.5}$ emissions from coal generation in India result in an estimated 112,000 deaths annually [66]. While improving the T&D system will indirectly reduce coal generation, we also found that there are system-wide benefits to reducing T&D losses. We estimate that compensatory generation in India alone can be reduced by 209 TWh annually (13.6% of 2018 total generation) when moving from the BAU to a high ambition scenario (capping T&D losses at 5%). The avoided electricity generation, potentially including coal, and consequent health impacts would likely be substantial [33].

Fig. 3 exhibits the variability of reductions in average emissions from compensatory generation from aggregate losses for countries with moderate ambition (reducing aggregate losses by 33%) and high ambition (capping aggregate losses at 5%) efficiency upgrades. These scenarios provide a lower bound on the expected losses that result from enhancements in the T&D system without generation investments and reflect changes associated with reductions in compensatory generation. When considering decreases in emissions from the BAU to high ambition scenario for aggregate losses for all countries, global median emissions decrease by about 40% (Supplementary Table S1). Improving aggregate T&D efficiency in all countries to the moderate or high ambition T&D efficiency have similar effects even though the mean global losses of the two scenarios are 8.3% and 4.8% respectively. However, there are some differences. SO_x emissions are predicted to experience slightly greater reductions for the high ambition scenario compared to BAU losses (44.1%), and $PM_{2.5}$ emissions are expected to have slightly fewer reductions (37.6%). Consequently, improving to the high ambition scenario would improve SO_x emissions slightly more and $PM_{2.5}$ emissions slightly less than CO_{2eq} and NO_x emissions.

As expected, we find T&D emissions savings are highly linked to generation types due to the relationship between compensatory generation and emission intensities of generation types. Typically, we see that countries with high levels of CO_{2eq} intensities (>670 g CO_{2eq}/kWh) have above average coal plant capacity (greater than 20%) (17 out of the top 30 CO_{2eq} intense countries). Meanwhile, countries with high levels of SO_x ($\geq$0.8 g SO_x/kWh), NO_x (>0.6 g NO_x/kWh), and $PM_{2.5}$ (>0.135 g $PM_{2.5}$/kWh) have greater than 15% oil plant capacity (27 out of top 30 SO_x intense countries, 21 out of top 30 NO_x intense countries, and 23 out of top 30 $PM_{2.5}$ intense countries). Some of the countries with high

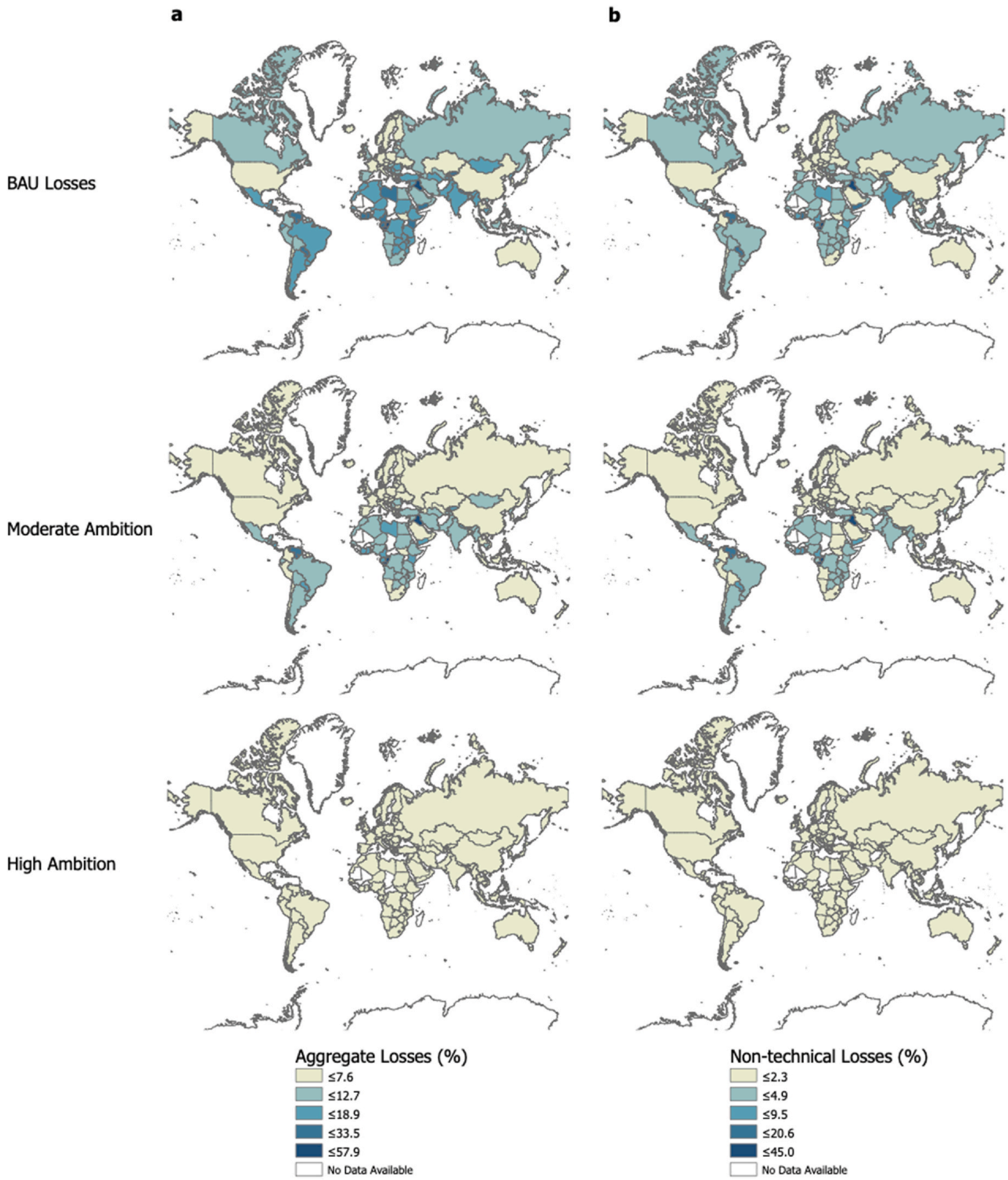

Fig. 2. T&D losses by countries for 140 countries for the BAU, moderate, and high ambition scenarios. a. Aggregate Losses, b. Non-technical Losses. Note that the aggregate and non-technical scales are not the same.

emission intensities also had percentages of non-technical to aggregate losses in the top 25% (26.5%) (Supplementary Fig. S5). We found that 8 of the 25 most CO_{2eq} intense, 8 of the 25 most NO_x intense, 9 of the 25 most SO_x intense, and 21 of the 25 most $PM_{2.5}$ intense countries to fit in this category. See supporting information for maps and tabular results.

For non-technical losses, we consider the BAU, moderate ambition (reducing non-technical losses by 33%), and high ambition (capping non-technical losses at 0.5%) scenarios. When transitioning from BAU for non-technical T&D efficiency to the high ambition scenario, median emission reductions range from 76% to 80%. Globally, nations could collectively reduce NO_x emissions by 286 kt, SO_x emissions by 375 kt, and $PM_{2.5}$ emissions by 405 kt annually (see Supplementary Fig. S2). CO_{2eq} emissions could be reduced by 210 Mt annually, which is equivalent to approximately 53 average coal-fired power plants in the United States. For the moderate ambition scenario, CO_{2eq} emissions could be reduced by 91 Mt (around 23 coal plants), NO_x by 121 kt, SO_x by 156 kt, and $PM_{2.5}$ by 179 kt each year. While national-level analyses present high-level guidance for country policies, we acknowledge there are subnational regulatory bodies, each of which makes decisions about infrastructure investments.

3.2. High-resolution analysis at subnational scales

We capture more granular results with subnational T&D

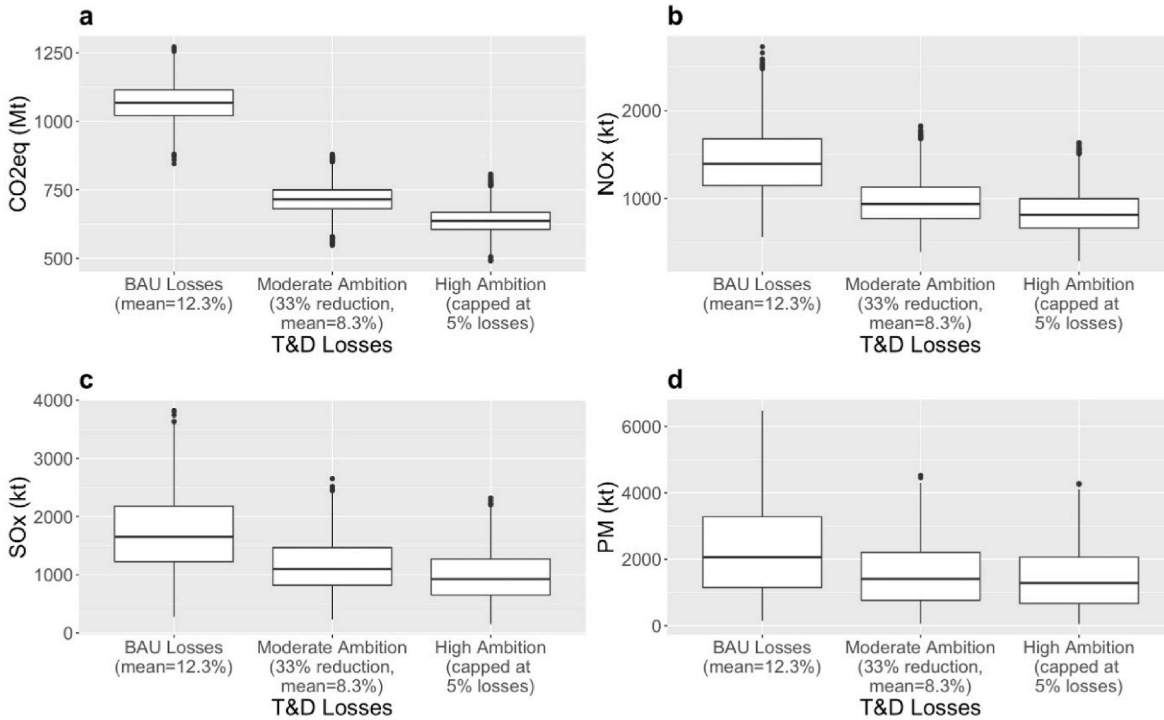

Fig. 3. Variability of annual air pollution emissions from aggregate T&D losses in the world including 142 countries from a Monte Carlo analysis with 10,000 trials. Box plots represent the 25th percentile, median, and 75th percentile. a. CO_{2eq} emissions, b. NO_x emissions, c. SO_x emissions, d. $PM_{2.5}$ emissions.

inefficiencies, providing a framework to assist countries in identifying mitigation opportunities for greenhouse gases and the resulting co-benefits from reductions in compensatory generation. We use the USA to examine compensatory average emissions at the subnational scale, supported by high data availability multiple subnational regulatory bodies, and large data availability on smart meter deployment and granular power plant data. The aim of this subnational analysis is to provide greater insight into how both technology and policy can be better designed to reduce air pollution and climate impacts. The value of this work is in highlighting how policy strategies change at the federal regulatory, and state levels.

Within the continental USA, aggregate T&D losses range from 2 to 5% across the states with the mean at 4.5%. When investigating the variability in total air pollutants from aggregate losses under BAU, moderate ambition (each state reduces aggregate losses by 33%), and high ambition (aggregate T&D losses capped at 2%) for the contiguous US, we find T&D improvements could reduce median compensatory emissions by at least 31% for all pollutants (Supplementary Table S3). When moving from the BAU to the very efficient scenario, CO_{2eq} and NO_x emissions reduced by 57.5%, and SO_x and $PM_{2.5}$ emissions reduce by about 53.5%. In the moderate scenario, the US could reduce CO_{2eq} emissions by 20 Mt/year, which is equivalent to 5 average US coal power plants running for a year. The other pollutants would reduce by approximately 0.3 Mt/year. Under the high ambition scenario, the US could reduce CO_{2eq} emissions by 35 Mt/year (approximately 8.8 coal power plants) and the remaining pollutants by 0.5 Mt/year. Within the very efficient scenario, we see wide ranges for annual air pollution emissions (CO_{2eq}: 24.9–62.3 Mt, NO_x: 13–121 kt, SO_x: 5–133 kt, $PM_{2.5}$: 3–266 kt), highlighting the impact of generation variability across states, thus reinforcing the need for more spatially resolved analyses.

Non-technical T&D losses range from 0.5% to 1.2% across the USA with the mean at 1.0%. When we consider the variability of air pollutants from non-technical losses under BAU, moderate ambition (each state reduces non-technical losses by 33%), and high ambition (non-technical T&D losses capped at 0.5%) for the contiguous USA, we find T&D improvements could reduce median non-technical compensatory emissions by at least 33% for all pollutants (Supplementary Table S4). From BAU to the very efficient scenario, CO_{2eq} and NO_x emissions reduced by 53.3%, and SO_x and $PM_{2.5}$ emissions reduce by about 49.5%. We see in the moderate scenario that the USA could reduce CO_{2eq} emissions by 4.6 Mt/year, which is equivalent to around 1.2 average US coal power plants annually. The other pollutants would reduce by approximately 7 kt/year. In the high ambition scenario, the US could reduce CO_{2eq} emissions by 7.4 Mt/year (1.9 coal power plants) and the remaining pollutants by approximately 10 kt/year.

Internalizing T&D emission externalities will impact market-level regulations and ultimately the consumer residential electricity prices. At the sub-national level, we first focus on the North American Electric Reliability Corporation (NERC) which is responsible for developing reliability rules governing the operation of the bulk power electric transmission systems. NERC develops and improves the reliability standards, enforces compliance for those standards, and distributes penalties for regulation violations. The NERC regions are a common sub-national level of aggregation for the United States when considering air pollution emissions from energy [67].

As seen in Table 1, the ReliabilityFirst Corporation (RFC), Western Electricity Coordinating Council (WECC), Midwest Reliability Organization (MRO), Northeast Power Coordinating Council (NPCC), and Southeastern Electric Reliability Council (SERC) have aggregate losses of around 4.78%, and Texas Reliability Entity (TRE) has aggregate losses around 5.09%. The losses of the NERC regions are area-weighted

Table 1
Aggregate losses of NERC Regions.

NERC Region	Business-*as*-Usual (BAU) Losses	Moderate Ambition Losses (reduced by 33%)	High Ambition Losses (capped)
MRO	4.76%	3.19%	2.00%
NPCC	4.77%	3.19%	2.00%
RFC	4.72%	3.16%	2.00%
SERC	4.87%	3.26%	2.00%
TRE	5.06%	3.39%	2.00%
WECC	4.76%	3.19%	2.00%

averages of the states' losses.

We find that regions with the most emissions on average from compensatory generation from aggregate losses (Fig. 4) and greatest losses (Table 1) differ. While the RFC has the lowest losses in the BAU scenario, it still produces high magnitudes of emissions. On the other hand, the TRE has the highest losses but produces lower magnitudes of emissions. This abnormality is likely due to the small region that TRE covers compared to other regions like the WECC. If the high ambition scenario is achieved, all regions would reduce their emissions below 15 Mt CO_{2eq}, 5 kt SO_x, and 2.8 kt $PM_{2.5}$. In the high ambition scenario, only the SERC for NO_x emissions remains in the class of high emission magnitudes (>21 kt). Within the NERC regions, state legislatures guide energy policy targets, which presents a need for understanding how state-level T&D efficiency targets will impact air pollution emissions.

In the USA, states often guide renewable energy targets and can provide incentives for investments to reduce air pollution emissions. Within the MRO region, North Dakota is the state with the highest emissions by intensity and magnitude (Supplementary Figs. S13 and S14). Thus, while a NERC level policy could target the MRO, similar emissions savings could be achieved through a state policy targeting North Dakota. Similarly, when we view the SERC region if there was a state policy then to secure the bulk of the savings policies should target Georgia, North Carolina, and Florida. Although TRE has low levels of emissions associated with compensatory generation, it presents a unique case due to it primarily encompassing one state and subsequentially being an islanded electricity system within the USA.

In comparing aggregate T&D losses (Fig. 5) to the subsequent emissions from these losses (Supplementary Fig. S14), we find that the states with the greatest magnitude of compensatory generation emissions do not always correlate to the states with the greatest aggregate T&D losses. In general, of the states with BAU losses above 5% (25 states), 12 states of those 25 have above-median BAU CO_{2eq} emissions (0.73 Mt, given all 50 states), 11 states for NO_x (0.11 kt), 8 states for SO_x (0.69 kt), and 11 states for $PM_{2.5}$ (0.16 kt). For example, North Dakota has low BAU aggregate losses (2.52%), but higher emissions in all scenarios. On the other hand, Texas has high BAU aggregate losses (5.06%), and higher emissions for all scenarios. This difference can likely be attributed to the generation profiles of these states. North Dakota primarily relies on coal, which heavily pollutes, and Texas strongly depends on natural gas and other fossil-fuels.

Additionally, the states that get little of their electricity from fossil-fuels tend to be in the lowest emission class for all pollutants and scenarios. We acknowledge that there is an inherent relationship between the emission intensity of generation types and the potential benefits of improving the T&D system because of the potential emissions shifts. We notice that states with high levels of CO_{2eq} (>490 g CO_{2eq}/kWh), SO_x (>0.18 g SO_x/kWh), and NO_x (>0.38 g NO_x/kWh) emissions per unit of electricity delivered have above average (>10%) coal plant capacity (7 out of top 10 CO_{2eq} intense states, 9 out of top 10 SO_x intense states, 8 out of top 10 NO_x intense states). Additionally, all the top ten states with the highest levels of $PM_{2.5}$ emissions per unit of electricity delivered either have >10% coal capacity (5 states) or >40% natural gas capacity (5 states). We find that Texas, with a relatively average efficiency for T&D systems within the USA (5.1%), is a high producer of air pollutants because 68% of its electricity is from fossil-fuels. Texas aggregate T&D inefficiencies correspond to 13.7% CO_{2eq}, 17.1% SO_x, 13.5% NO_x, 20.2% $PM_{2.5}$ of emissions due to compensatory generation in the USA. There are other states with more of their electricity generated from fossil-fuels; however, they either do not generate as much electricity as Texas, or they have more efficient T&D systems. Texas' issues like the rolling blackouts induced by the deep freeze in 2021 are caused by Texas' system being in islanding mode [68]. Due to its island mode, the responsibility for spending on the physical infrastructure can fall at the NERC, the Electricity Reliability Council of Texas, or state levels.

Even under the high ambition scenario for aggregate losses, Texas is still the largest producer of all air pollutants, based on median emissions estimates. The range in emissions estimates that result from compensatory generation varies within the top five of the most populated states–California, Texas, Florida, New York, and Pennsylvania (Supplementary Fig. S15)–signifying the importance of conducting analyses at more granular scales for solutions. If Texas moves from BAU (5.1% aggregate losses) to the high ambition scenario, compensatory generation would decrease by 11.5 TWh and median emissions for all pollutants by 60%. In a high renewable energy investment scenario, the compensatory generation savings would correspond to 7.7 GW of residential solar investments. The top five most populated states have aggregate T&D losses above 5.1% except Pennsylvania, whose losses are 3.7%. Yet, its median emissions are not always the lowest due to the state's heavy reliance on coal (6.1% of generation) and natural gas (42.0% of generation). While improving the T&D system will indirectly

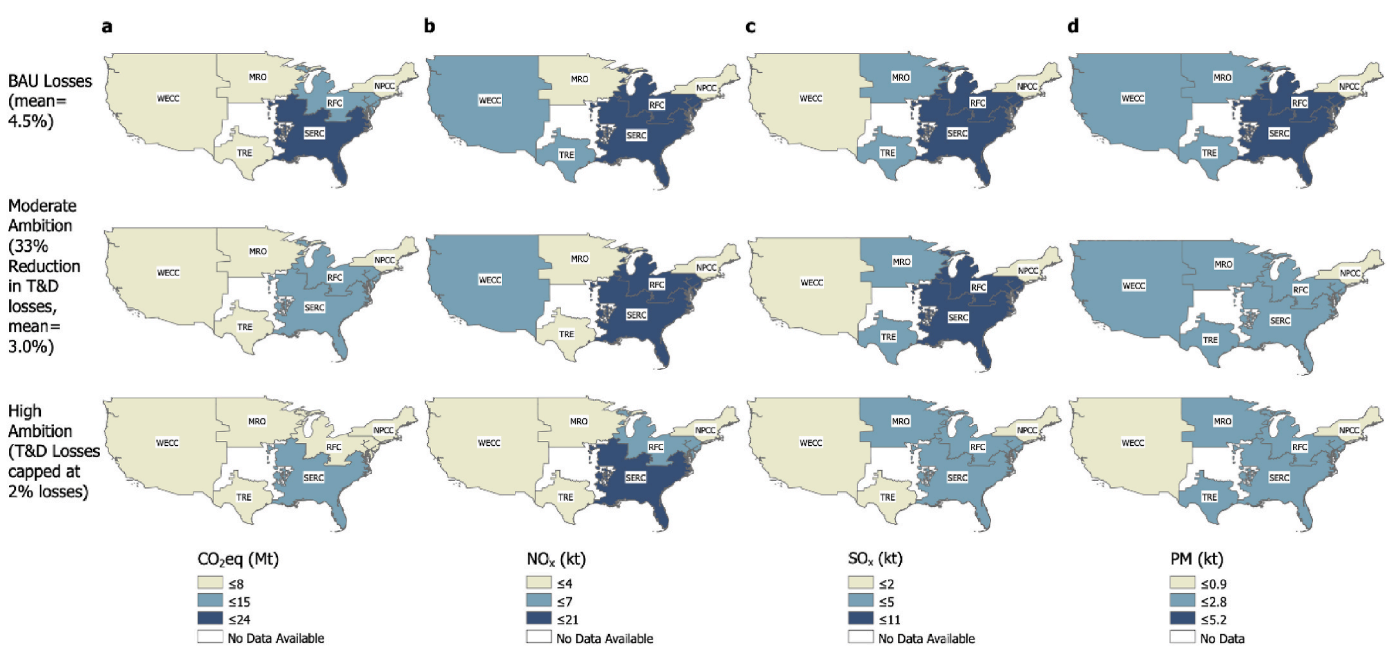

Fig. 4. Emissions due to aggregate T&D losses by NERC Region, a. CO_{2eq} emissions, b. NO_x emissions, c. SO_x emissions, d. $PM_{2.5}$ emissions.

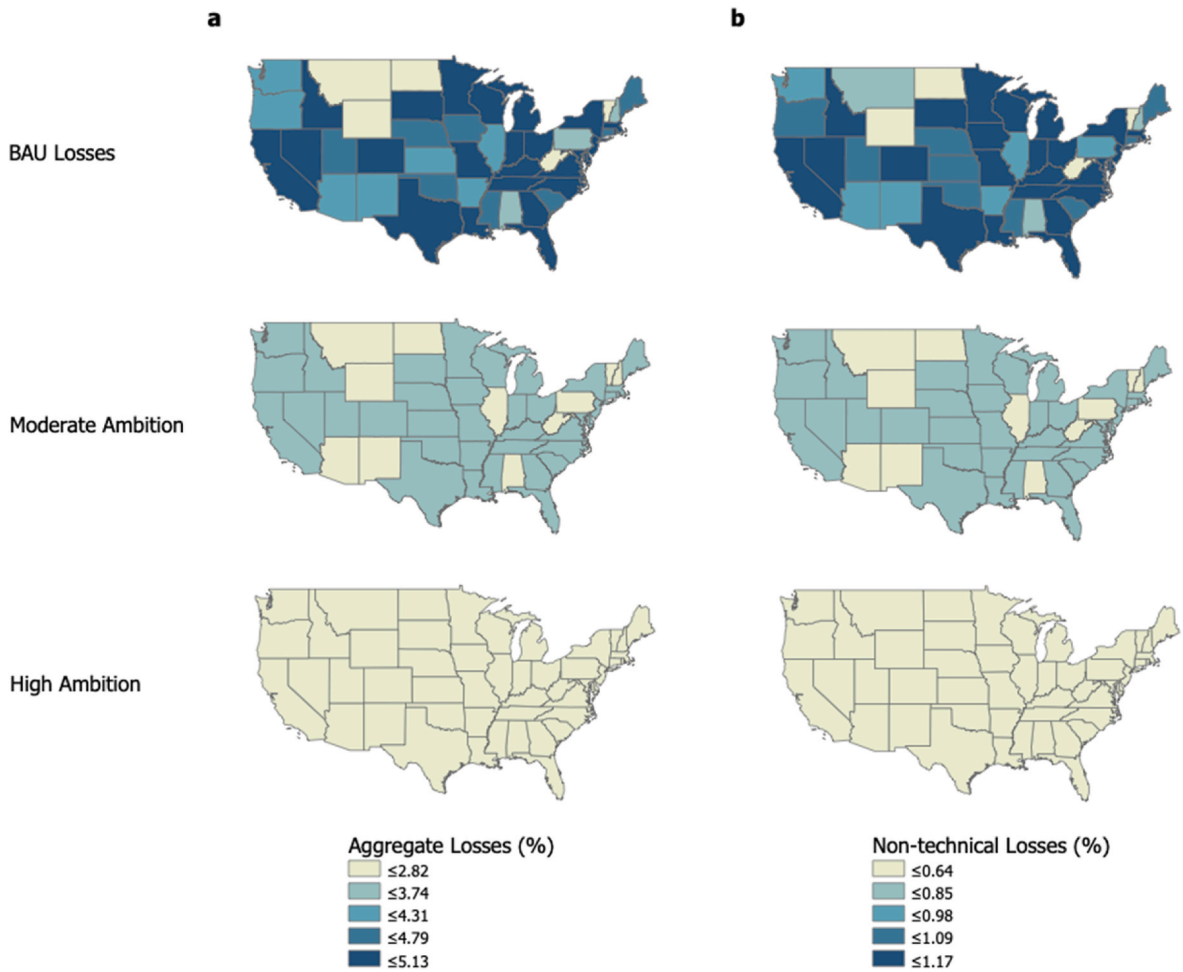

Fig. 5. T&D losses by state for the BAU, moderate, and high ambition scenarios. a. Aggregate Losses, b. Non-technical Losses. Note that the aggregate and non-technical losses scales do not overlap.

reduce coal or natural gas generation, we also found that there are system-level benefits to reducing T&D losses. If Pennsylvania followed the high ambition scenario, this change would reduce compensatory generation needs by 3.1 TWh and reduce Pennsylvania's BAU annual emissions by 46%. This change corresponds to a reduced need for 2.6 GW of residential solar investments. Thus, it is important to recognize that while improving T&D losses will not completely compensate for relying more on fossil-fuels, it can reduce BAU emissions and the number of resources needed in a fully renewable electric system.

3.3. Initial deployment cost for CO_2 reduction comparison

In the USA, non-technical losses will primarily be reduced through the deployment of more effective billing systems (i.e., smart meters). We considered the initial deployment and total costs of three different carbon mitigation strategies: installing smart meters to support the existing grid, constructing more wind turbines, and constructing solar farms. While multiple green technologies can be used to reduce emissions from the electric grid, we focus on solar and wind because these technologies are the most common renewable technologies planned to be constructed in 2022 [69]. While solar and wind is rapidly expanding across the globe, the cost of renewable energy deployments is uncertain [70,71]. Hence, we include smart meters in our analysis which are often a cheap, efficient, and a widely deployable technology [58]. Smart meters reduce non-technical losses by providing more accurate billing, reducing the use of faulty meters, and preventing electricity theft [18,72]. We assume that between 2 and 40% of energy reductions that are due to smart meters are reductions to non-technical losses according to past installations of smart meters [57]. We also assume that more accurate billing and reducing the use of faulty meters will not increase demand. To quantify improvements by smart meters, we assume that smart meters can reduce household electricity consumption by 6% [19]. We consider two scenarios for smart meter deployment when considering the total costs: moderate ambition (reducing non-technical losses by 33%) and high ambition (capping non-technical losses at 0.5%).

One way to compare the viability of carbon reduction options is to consider the initial deployment cost for CO_{2eq} reduction of each option in the United States. These values are different than the abatement costs reported by the IEA ($27.10/t CO_{2eq} for wind power and $32.98/t CO_{2eq} for solar PV) and other sources because typically operational losses and savings from adopting the technologies are included in the analysis [73]. We note that only considering the initial deployment or construction costs is relevant to implementation of the Infrastructure Investment and Jobs Act (2021) and the Inflation Reduction Act (2022) because it will generally fund construction of new energy technologies rather than the operations costs and will not receive benefits from the savings of the new technologies [74,75].

Our analysis of the initial deployment cost for CO_{2eq} reductions of installing more smart meters, wind turbines, and solar plants. Our analysis considers a 2.42 MW wind turbine operating with a capacity factor of 35% and a 10.05 MW solar plant with a capacity factor of 24%, which are meant to be average in the United States. We also focus on the upper bound of our estimate to illustrate how smart meters can reduce non-technical losses. Reducing non-technical losses through wind turbines (2.5–10 billion) appears to be the most viable solution, when solely looking at the initial deployment (or construction) costs. Smart meter median initial deployment (or construction) costs range from 5 – 14.5 billion, and solar costs range from 5 to 23 billion. As a note, this methodology is an upper bound and is different from the abatement cost methodology. It does not consider operational cost changes between wind, solar, and fossil fuel generators.

In 2019, there were approximately 22 million traditional residential and 41.2 automated meter reading meters in the United States [21]. As of 2019, 87.5% of the total number of meters in the USA were in the residential sector, while another 12.0% of total meters were in the commercial sector [21]. To achieve the CO_{2eq} reductions of the moderate ambition scenario (reducing by 12.0 TWh or 4.6 Mt CO_{2eq}, see Table S4), the nation would need to deploy approximately 25.7 million advanced metering infrastructure units (smart meters) at a median deployment cost of $7.07 billion.

For the high ambition scenario (reducing by 19.3 TWh or 7.5 Mt CO_{2eq}), the nation would need to deploy approximately 41.3 million smart meters at a median cost of $11.4 billion. To achieve deployment of 41.3 million, there would need to be a total replacement of the 22.0 million traditional residential meters, but at least 19.3 million smart meters would still be needed. A combination of replacing meters in the commercial and industrial sectors, and potentially other technology deployments (e.g., renewable generation, efficient appliances) could be used to achieve the remaining carbon reductions. In the moderate ambition scenario, wind turbines (median cost of $3.02 billion) and solar plants ($5.49 billion) are less costly compared to smart meters. For the high ambition scenario, we estimate that smart meters are less costly compared to solar plants ($15.6 billion) but not wind turbines ($8.54 billion).

These cost estimates do not consider operational costs or savings from adopting the technologies, which tell a different story than looking at deployment costs alone. In recent years, there have been declines in the levelized cost of energy in solar and wind. Reported values of abatement costs have been found to range from -$7 and $70 per tCO_{2eq} for wind and from $41 per tCO_{2eq} to over $100 per tCO_{2eq} for solar technologies, depending on assumptions [76]. Despite the relatively high initial construction costs, it is well known that the operational revenues from wind make it competitive on the market since there are no fuel costs. This fact is supported by the levelized cost of electricity (LCOE) for onshore wind being $37.80/MWh, and standalone solar being $36.09/MWh, compared to natural gas combined cycle being $37.05/MWh [77]. While installing smart meters could be a viable solution in the United States for reducing non-technical losses, their viability in a global context may be stronger than in the USA. In some parts of the world with governance challenges or a “culture of corruption,” certain groups can expect to not pay for their electricity and get away with it [33]. This problem results in fraud, stealing electricity, billing irregularities, and unpaid bills, which together contribute to a large share of a country’s non-technical losses [33]. Smart meters are an effective strategy in reducing theft because it introduces automatic billing payments and provides more accurate and transparent billing. While many countries like India have passed legislation to expand the legal understanding and repercussions of electricity theft [18], these countries still have problems with electricity theft [33,78]. Thus, installing smart meters can reduce electricity demand and reduce losses that occur due to electricity theft.

There is a large amount of variability for the smart meter estimate, which may result from cost differences between manufacturers or purchasing smart meters in bulk [58]. Another point to keep in mind is that the performance of solar plants and wind turbines is dependent on the weather. Thus, before implementation, a high-resolution analysis of resource constraints and smart meter costs in the area should be conducted. We note that countries are using a combination of approaches (smart meters, wind, and solar deployment) as part of their decarbonization strategies. Smart meters might be cheaper in some cases, and the right combination of smart meters, wind, and solar should be based on spatially resolved analysis. While renewable energy has other benefits beyond reducing carbon emissions, even in a high renewable future, smart meters can be beneficial because they will reduce the electricity demand, leading to fewer investment needs in generation capacity.

4. Conclusions and policy implications

Analyses that clarify the link between grid inefficiencies and air pollution are necessary to determine not only the mitigation potential but also formulate a holistic strategy for reducing emissions. Through quantifying the air pollution emissions associated with T&D losses in 142 countries, we determine the mitigation potential, and we leverage an in-depth analysis for the USA to inform how to reach this potential. Our analysis presents a first-of-a-kind approach that emphasizes the need for high spatial resolution, granular analyses and realizes the co-benefits of reducing air pollution emissions and resolving grid inefficiencies. Decisions to invest in infrastructure are made at multiple regulatory levels, including scales that country-level analyses are incapable of capturing. Reducing harmful pollutants from grid inefficiencies needs to capture the emissions and energy savings opportunities from regulations and investment strategies from the scale of countries down to each facility.

For aggregate losses, our multinational and subnational analyses tested moderate ambition (reducing regional losses by 33%) and high ambition (reducing each country to 5% T&D losses, or state to 2% T&D losses) scenarios at multiple scales. Our country-level analyses of non-technical losses also considered moderate ambition (reducing regional losses by 33%) and high ambition (reducing each country to 0.5% T&D losses) scenarios. These scenarios provide a lower bound on the expected number of losses that can result from enhancements in the T&D system without generation investments.

Our work has three implications for policymakers involved in decarbonizing the electricity sector. First, our results point to the need for systems-level examinations of air pollution emissions and mitigation at national and sub-national scales. Only a few countries consider T&D in their 2015 NDCs [2], meaning that countries are not capturing the full range of grid-scale solutions.

Second, as the electricity system is going through major transitions to reduce emissions, multiple co-benefits arise from viewing the whole system at multiple scales. Grid modernization initiatives that reduce T&D losses can reduce the emissions impact of the top emitters within a country while lessening the resource needs for investment in renewable energy technologies as seen in our analyses of Texas and Pennsylvania. Future work could consider how electricity demand would change as technical improvements to the T&D system are made, and the trade-offs between other environmental considerations [5,79] (e.g., water consumption and land use [80,81]). Other work could further investigate the health benefits of the reductions in air pollutants from T&D losses, consider the equity of the distribution of these benefits [82], and look deeper into emerging economies [83].

Third, we have highlighted that public policies at varying scales can each benefit from reducing T&D losses. These benefits stem from the linkages between T&D infrastructure, air pollution emissions, and material requirements needed in the low-carbon energy transition [14]. In the USA, T&D loss reductions would come from reducing distances between suppliers and consumers (i.e. decentralized generation), technical losses (e.g., improving quality of lines or transformers), and non-technical losses (e.g., enhancing billing security and restructuring electricity system regulation). Even highly efficient electricity systems (<6% T&D losses) can have non-technical losses that range from 1% to 2% [33]. Smart meters reduce overall electricity system demand (i.e., the sum of T&D losses, customer demand, poor billing practices, and theft), due to better bill accounting. This change in demand in turn decreases the amount of investment needed in new energy sources and non-technical losses. We found that smart meters are less cost-effective than wind turbines when reducing carbon emissions from non-technical losses, due to wind turbines being at the community scale. However, smart meters are more cost-effective compared to solar plants in the high ambition scenario.

An additional consideration is that the benefits from wind and solar are resource-dependent, while smart meters provide benefits by making the billing process more reliable. In 2018, the USA had reached a 56% adoption rate of smart meters, and by 2020 the USA had reached approximately 75% adoption [20,21]. Thus, replacing the final 25% is an important step towards reducing emissions from non-technical losses. Future studies should investigate the T&D emissions mitigation potential within a developing country context and distinguish between technical and non-technical losses. Additional work could also consider how alternative energy sources, besides wind and solar, compare to deploying smart meters.

In conclusion, our approach can not only be used to quantify the regional benefits of reducing overall grid inefficiencies but also to estimate the costs of technological changes to reduce grid inefficiencies. This work highlights the impetus for greater data availability and the need for higher resolution energy transition analyses at multiple regulatory scales due to multiple stakeholder groups operating in these areas [84,82]. While this work focused on the USA, other high-efficiency countries have multiple sub-national electricity regulatory structures. Reducing T&D losses at multiple levels, not only reduces compensatory emissions but also may reduce the investments need in a low-carbon energy transition. Considering the impacts of T&D losses is vital in a transitioning electricity system in both the BAU system for T&D efficiency and in a low carbon or carbon-neutral future.

Credit author statement

LJ: Formal analysis, Data curation, Writing – original draft, Validation, Visualization DN: Conceptualization, Methodology, Validation, Writing – original draft; KS: Conceptualization, Methodology, Writing – review & editing; SJ: Conceptualization, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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