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Assessing county-level vulnerability to the energy transition in the United States using machine learning

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ABSTRACT

Energy sector decarbonization will play a critical role in society's attempt to minimize climate change. This transition will unavoidably involve economic disruption to communities that rely on fossil fuels for jobs and economic activity. In this work, we assess the economic vulnerability of counties across the contiguous United States to the energy transition using a novel methodological approach that combines exposure through reduction in energy employment and socio-economic sensitivity due to a lack of adaptive capacity during the energy transition. Using machine learning clustering, we first identify county-level exposure to negative employment shocks. We then develop and implement the Resilience during the Energy Transition Index (RETI) to measure county-level sensitivity and adaptive capacity and compared this Index across employment clusters. We find that counties in coal mining clusters are significantly – and uniquely – less able to cope with economic distress. We also apply our framework to a case study focused on three of the states in Marcellus-Utica shale plays: Pennsylvania, Ohio and West Virginia. The results of this case study support the argument that financial and infrastructure boosts from non-renewable energy extraction and utilization build resilience only if they are used to building capital for the post-carbon economy, providing further evidence of the conditions required for fossil fuels to serve as bridge fuels towards a low-carbon economy.

1. Introduction

Over the past two decades the United States (US) energy sector has experienced substantial shifts in the fuel mix and the number of people employed in it. From 2002 to 2017, employment in the energy sector grew by 33 % (from 1.72 to 2.62 million full time equivalents - FTEs). This growth was largely driven by the oil and gas industry, nearly doubling the number of people employed within the sector, with a 96 % increase. However, despite this overall growth, the coal mining, fossil-fuel power and hydropower generation sub-sectors lost more than 137,000 net FTEs in this period [1]. These employment trends mimic the production of these sub-sectors with natural gas production growing from 18.9 to 27.3 Tcf³ and coal production peaking in 2008 at 1172 M short tons, before falling to 775 in 2017 [2]. For electricity generation, the share of coal in the US grid fuel mix fell from 50 % in 2002 to 30 % in 2017, while natural gas rose from 18 % to 32 %.

In the absence of full-scale deployment of carbon capture technologies, electricity sector decarbonization will require continuing this decline in coal extraction – and reversing the growth of natural gas – as we move away from carbon-intense fuels. These shifts away from fossil fuels will have uneven economic impacts across the US with negative impacts likely to be highly concentrated in communities that rely on fossil fuel industries for their economic well-being. There were 17,741 fewer net FTE in coal mining nationwide in 2017 when compared to 2001; these losses were concentrated in a handful of states like Kentucky (7801 representing 44 % of the net lost FTE), West Virginia (2898 or 16 %), Pennsylvania (2304 or 13 %), Virginia (1864 or 11 %) and Ohio (1014 or 6 %). The net growth of renewable jobs (12,120 new FTE in 2017 compared to 2001) is also geographically concentrated with almost two-thirds of new FTEs located in Texas, California, Illinois, North Carolina and Florida [1]. This highlights that while energy sector employment is growing, this growth is not evenly distributed.

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The just transition framework offers a way to conceptualize the benefits and costs for individuals and communities during energy decarbonization and how impacts are distributed across society. Originally developed to reconcile green development with the needs of workers [3], it has since expanded to include coordination between climate, environmental and energy justice [4]. As the concept of the just transition has matured, it has highlighted the need to respect principles of: (1) equitability of impact in the distribution of benefits and costs, (2) meaningful engagement and fair representation in decision-making and (3) deliberate efforts to repair past harms to historically minoritized communities [5]. Given these principles, there are two dominant definitions of a just transition in the literature: one that calls for protection and investment in minoritized communities during decarbonization and a second that argues for attention to be paid to those communities that currently depend on fossil-fuels for their economies [6].

Leveraging analysis of employment data to investigate vulnerability at the county-level can reconcile these different just-transition discourses. However, existing county-scale employment analyses are focused on specific industries, regions, or short periods with vulnerability or resilience components. Haerer and Pratson [7] found no correlation between counties losing jobs and those gaining from growing renewable industries between 2008 and 2012. However, their economic input-output (I-O) analysis of the electricity sector excluded non-fossil dispatchable generation, meaning their work misses the decline of hydropower. Other county-scale work has studied localized socio-economic effects like the relationship of coal and poverty [8], economic spillover effects to neighboring areas during coal booms and busts [9] and culture-based adaptation processes to the transition [10] in the Appalachian region. Similar work has explored the economic effects of concentrated coal production cycles in Western Canada [11]. Taken together, this literature indicates that employment in fossil fuel industries reflects exposure to the transition and can be further analyzed in comprehensive vulnerability studies.

Contrasting county-level, energy employment across sub-sectors is critical in creating a just transition framework capable of capturing impacts that top-down I-O analyses or bottom-up, technology-focused studies are likely to miss. In an I-O study across the US, Garrett-Peltier [12] found that investing in renewables and energy efficiency can generate around three times as many short- and medium-term jobs as investing in fossil fuels. Energy employment meta-studies describe that bottom-up employment analysis typically focus on only one technology or sector (e.g., installing wind turbines or retiring coal-fired power generators), so they do not study interactions across sectors [13]. Other bottom-up analytical models do not typically account for indirect jobs [14]. Both bottom-up and I-O methods miss spatial variation and inter-sectoral/technology interactions that well-designed county-level studies can account for. Furthermore, as highlighted in the meta-study performed by Wei et al. [13] there are substantial difficulties in aggregating and comparing cross-technology analysis from different sources and methodologies. In addition to accounting for geographical disparities and technology disaggregation, county-scale analyses of energy sub-sector employment also respond to growing interest in subnational studies of the just energy transition [15] and to recommendations that focus on the perspective of individual households in the measurement in sustainable development studies [16].

Machine Learning (ML) can provide efficient tools to discover patterns and trends over multiple periods in the large datasets that are required to study employment or economic dependence at the county-level. Data at this spatial and sectoral resolution can contain tens to hundreds of features (e.g., employees or revenue by economic activity) in sets of more than 3000 elements (i.e., the US counties) for different years. While ML has previously been used to analyze the structure of the energy economy (e.g., effects of interventions on consumption patterns), its main applications in energy policy have focused on supervised ML to predict prices or model the market [17]. Unsupervised ML (e.g., clustering) is less frequently used for energy analysis than supervised ML

and has almost exclusively been used for demand response scheduling [18], energy efficiency, assessments of consumption patterns [19] and anomaly detection in infrastructure operation [20]. In the energy policy field, Csereklyei et al. [21] used Gaussian Mixture (GM) clustering to compare changes in national electricity fuel mixes across the European Union over time. As part of that work, Csereklyei et al. identified a relationship between being a high-income country and having an energy mix with more highly desirable energy sources (e.g., electricity generation or natural gas vs coal and biomass). In the economic development field, Khalaf et al. [22] use unsupervised ML to categorize US counties to create a novel and more nuanced classification of rurality. The authors used hierarchical clustering to identify groups of counties with similar potential economic development strategies, based on their natural resources, opportunities and challenges – including industrial dependency. By using ML to study potential employment losses during the energy transition, we propose to create a framework for county-level assessment of vulnerability during energy transitions.

County-scale vulnerability scoping assessments can inform models of local community resilience and guide transition policy interventions. These assessments focus on three dimensions of vulnerability to a disruptive event: exposure, sensitivity and adaptive capacity [23,24]. Exposure is defined as the potential to be negatively affected by a disruptive event. Sensitivity describes the magnitude of impact from the disruptive event. Adaptive capacity is a measure of the ability to resist and recover from the shock of the disruptive event. Researchers and decision makers frequently build vulnerability assessment models that measure local- and county-level elements to identify disparities and analyze state and federal policy interventions. However, few studies have assessed the dimensions of vulnerability in the context of the energy transition. Raimi et al. [25] map county-level exposure and sensitivity based on fossil-fuel economic activity and a climate and economic justice index, respectively [26]. They identify locations that should be targeted by policy makers for interventions to further develop adaptive capacity as the transition advances. Carley et al. [27] evaluate vulnerability to energy price increases due to renewable portfolio standard implementation and regional disparities in vulnerability. Snyder [28] produces first-order, county-level estimates of vulnerability to decarbonization while arguing that such work can guide investments to high-risk areas. Many vulnerability assessments (especially those in assessing climate change vulnerability) use demographic and household economic variables (e.g., age distribution, ethnicity, unemployment and transportation) that influence short-term responsiveness following a disruptive event [29–31]. To measure these variables, past work has used socio-economic metrics that describe components of economic development, social capital, communication infrastructure and access, self-determination and community engagement [32]. In this paper, we propose to use data on socio-economic conditions and renewable energy to describe sensitivity and adaptive capacity during the energy transition.

In this work, we reconcile two of the leading frameworks in the just transition literature in a novel vulnerability assessment combining job-loss exposure with socio-economic resilience. To integrate the vulnerability scoping assessment with the exposure clustering algorithm, we have created the *Resilience during the Energy Transition Index* (RETI), a framework capable of providing county-level insight on the ability of counties to benefit from the transition away from fossil fuels. The RETI framework is based on socio-economic, policy and renewable electricity resource data. With this framework, we capture patterns of exposure and characterize differences in economic resilience during the transition away from a fossil energy-dependent economy. Finally, we analyze the level of resilience associated with different transition paths and energy policy interventions to effectively build resilience for the energy transitions. Our methodology allows us to identify typologies of counties based on how they rely on energy employment and to contrast the evolution of socio-economic resilience to shifts in energy production and use (e.g., the shale gas boom and the decline of coal).

2. Methods

We synthesize energy dependence with county resilience into an assessment of vulnerability in the face of the energy transition. The core of our analysis (Fig. 1) is the application of the RETI metric on clusters of counties that are similarly exposed to economic disruption during the energy transition. To do this, we analyzed employment data from four years over a 16-year period (2002, 2007, 2012 and 2017) to analyze the decline of carbon-intense energy extraction and utilization activities across 12 different energy sub-sectors. We then created and normalized indicators of sensitivity and adaptability based on socio-economic, policy and renewable resource data into the RETI score for each county in the continental US. Finally, we compared cluster-specific RETI distributions to identify differences in county resilience between clusters that rely on fossil fuels and those that do not.

2.1. Data description

We analyzed data from five sources that describe county-level conditions for our exposure analysis in 2002, 2007, 2012 and 2017 and to create the RETI for 2017 in every county of the 48 states of the contiguous US. Alaska and Hawaii were not considered for the RETI due to a lack of data availability on wind-powered generation potential and on existing renewable policy instruments – but are included in the clustering analysis. Further details of the data sources can be found in the Supporting Information (SI) Section 1 with the variables used in the RETI described in Table S1.

2.1.1. State- and county-level economic data

We use IMPLAN (IMPact analysis for PLANning), a state- and county-level dataset that reports the number of jobs and industry output, proprietor income and output volume in US dollars for 536 economic sectors. Using correlation analyses (details in SI Section 2 and Table S2), we chose an initial set of 18 energy-related sectors from which we down select to identify 12 representative sectors for our clustering model.

These 12 sectors include activities in resource extraction (coal mining and oil and gas well drilling), power generation (nuclear, fossil fuel, wind, solar, biomass, hydropower, geothermal and other power generation), transmission and distribution (T&D) and turbo-generator manufacturing. We base our analysis on the number of jobs for each county in these 12 sectors.

2.1.2. Socio-economic variables

The United States Census Bureau (USCB) provides county-level information about population and economic conditions through its annual American Community Survey. We leverage this USCB survey for data on educational attainment, poverty, unemployment and household internet connectivity [33,34].

We also used percent change in gross domestic product (GDP) from 2017 to 2018 as reported in Real Gross Domestic Product by County, 2016–2019 dataset from the US Bureau of Economic Analysis [35].

2.1.3. Renewable resource potential

We used the county average of rasterized data for wind speed at a 100-m hub height and Direct Normal Irradiance (DNI), both datasets available from the National Renewable Energy Laboratory, as proxy measures of the amount of potential wind and solar power available in a county [36–39].

2.1.4. Renewable energy policy

The Database of State Incentives for Renewables and Efficiency (DSIRE) is a source of information on renewable energy and energy efficiency policies across the United States managed by the North Carolina Clean Energy Technology Center [40]. DSIRE tracks 45 types of federal-, state-, city-, county- and zip code-level policies, as well as incentives and programs from non-profits and utility companies. We selected 23 policy types that are most directly related to renewable energy development including renewable portfolio standards, tax incentives and net metering policies. These policies are then disaggregated to the county-level (detailed information in SI Section 3 and Table S3).

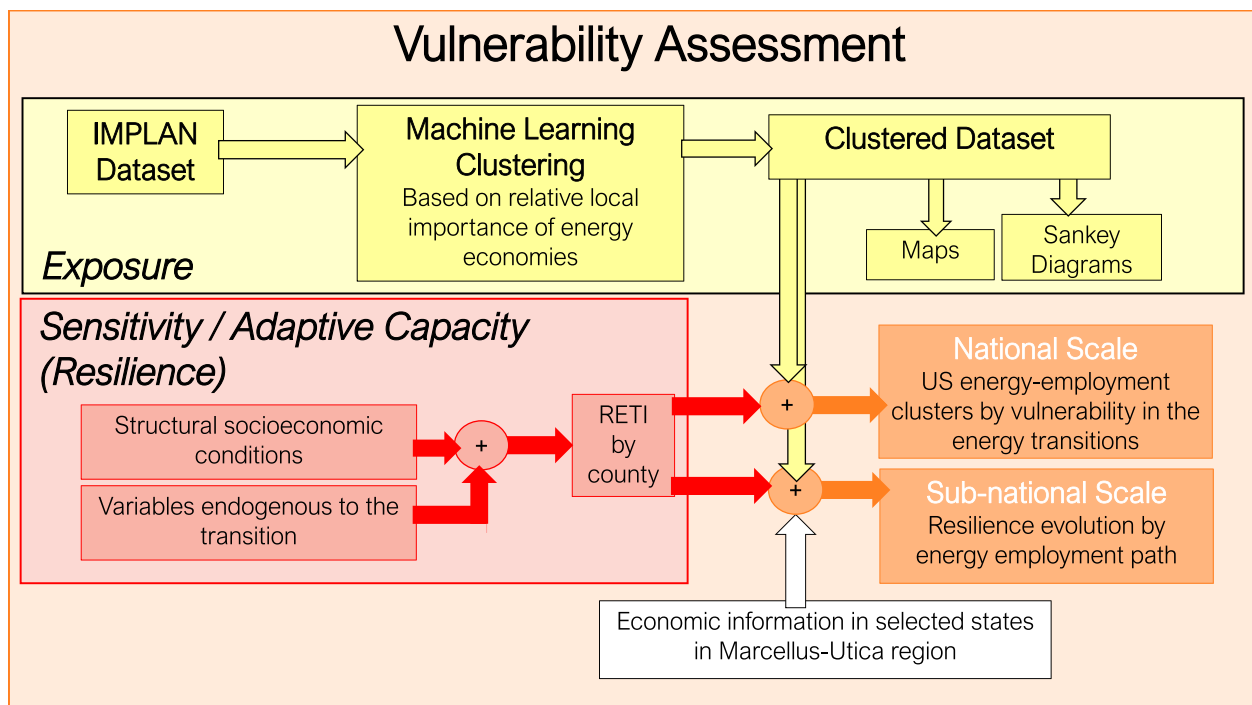


Fig. 1. Methods for the vulnerability assessment. The exposure dimension (yellow) relies on a machine learning clustering model based on type and degree of reliance on energy activities for employment. The RETI metric assesses the sensitivity and adaptability dimensions of vulnerability (red). We perform this analysis across the entirety of the contiguous US. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.2. Clustering US counties on the basis of energy sectors employment

We applied model-based clustering on normalized county-level employment data to identify groups of counties that depend on the same (or similar) energy sub-sectors for employment. We first normalize county-level employment data in energy sub-sectors relative to the largest employer sector in the county (Eq. (1)).

$$e_{c,t,i} = \frac{E_{c,t,i}}{E_{c,t,max}} \quad (1)$$

The normalized employment in county c in year t in energy sub-sector i ($e_{c,t,i}$, unitless) is calculated as the ratio of the absolute number of people employed (in [FTE]) in energy sub-sector i ($E_{c,t,i}$) to the number of jobs (in [FTE]) in the sector with the highest employment ($E_{c,t,max}$) in county c and year t . The sector with the highest employment can be a non-energy sector, so $e_{c,t,i}$ acknowledges the relative importance of energy industries in the county's entire economy. We then used a GM clustering algorithm to sort the 3141 counties and county-level equivalents in all 50 states based on $e_{c,t,i}$.

We selected the GM clustering technique and tuned the model based on its performance for our data. The GM technique is preferred when clusters may differ in shape, size and orientation in the feature space [41,42] and has previously been used when the variables are not necessarily normally distributed [21]. Furthermore, the GM type we selected (tied covariance) provided high clustering quality in our data according to the Silhouette index [43]. Finally, we calibrated the number of clusters to be 12 using the elbow criterion [44–46]. Details on the design, parameters and performance of our GM clustering model can be found in SI Section 4 and Figs. S1 and S2.

We identified the cluster based on the type and intensity of the energy employment. We labeled the clusters (e.g., “Coal – Medium”, “Natural Gas – Low”) after the most important energy sub-sector (i.e., the one with the highest normalized average) – defining archetypes that we tracked in later years. We labeled a cluster as “Low” if, on average, the most important energy sub-sector had less than one-third, as “Medium” if the number of people employed by the sector was between one and two-thirds and as “High” if it employed more than two-thirds of the number of people employed in the county's highest employment sector.

2.3. Modeling historic transitions in the energy sector

We observed employment evolution patterns using an interpretable cluster tracking method and a Sankey diagram. As new clusters appeared over time, we checked for similarity with the archetypes defined in previous years [47] using the Fowlkes-Mallows similarity metric [48] between periods. Since our labeling method did not rely on an a priori rule, but instead on similarity, we had flexibility to distinguish intra-cluster changes over time (e.g., if the average $e_{c,t,i}$ of the dominant energy sub-sector rose or declined) while identifying county migration between clusters [47,49]. Finally, we created a Sankey diagram to show cluster size and the movement of counties between clusters over our study period.

2.4. Analyzing county-level sensitivity and adaptive capacity for the energy transition

Finally, we characterized county-level sensitivity and adaptive capacity with the RETI. The RETI combines eight variables that describe community sensitivity to economic shocks and ability to adapt to a renewable energy economy. The four community sensitivity variables included: (1) percent of children in poverty, h (in [%]), (2) annual GDP growth, g (in [%/yr]), (3) the unemployment rate of the labor force 16 years or above, u (in [%]) and (4) the population over 25 without any college education, e (in [%]). The four variables that describe community ability to adapt to new renewable energy economic models

included: (5) households with internet access, i (in [%]), (6) annual average DNI, s (in [W/m²]), (7) average wind speed at a 100 m hub height, w (in [m/s]) and (8) number of pro-renewable policy programs, p . The first five variables are standard metrics for community resilience [31,32,50] and the last three variables are specific to the energy transition.

While we designed the RETI metric as a representation of community resilience specifically for the energy transition, we have drawn on the energy economy, hazard and climate literatures. The variables we have chosen are frequently used in these fields and include education [27,28,31,32,50,51], infrastructure and communication [23,28,31,51,52], household and infant poverty [28,29,31,52–54], unemployment [28,29,31,52] and economic growth [24]. We also use the number of policy mechanisms and renewable resource bases as a proxy for potential renewable job creation (rather than relying on highly uncertain future employment forecasts), given that jobs in renewable energy generation are less likely to exist where renewable energy resources and supporting policy are limited. The number of policy instruments is a measure of likelihood for future developments and the resource variables reflect a measure of the maximum achievable capacity by county. In SI Section 5 (and Table S4), we further describe the selection process of the RETI variables including a sample list of variables used in the literature to measure community sensitivity and adaptive capacity.

To create the RETI, we first normalized each of the input variables to be between 0 and 1. This normalization assigns the lowest-observed value to be 0 and the highest-observed value to be 1 with remaining values interpolated between these extremes (Eq. (2)).

$$x'_{c,t} = \frac{x_{c,t} - \min(x)}{\max(x) - \min(x)} \quad (2)$$

Here, $x_{c,t}$ is the variable of interest for county c in year t and $x'_{c,t}$ is the normalized variable. We then calculate the RETI for every county in the contiguous 48 states (Eq. (3)). The RETI is a non-weighted metric that adds measures related to adaptive capacity and subtracts measures related to sensitivity. We do not add weights to individual variables in the RETI formula to avoid including additional parameters and their corresponding uncertainty in our model, consistent with the literature on building linear models [55].

$$RETI_{c,t} = i'_{c,t} + s'_{c,t} + w'_{c,t} + p'_{c,t} - h'_{c,t} - g'_{c,t} - e'_{c,t} - u'_{c,t} \quad (3)$$

As the RETI metric is not normally distributed (results of the Kolmogorov-Smirnov tests in SI Section 6 and Fig. S3), we used a non-parametric Mann-Whitney-Wilcoxon (MWW) test to determine if there are significant differences in the distribution of county-level RETI scores between clusters [56].

3. Results

3.1. County-level energy employment in 2017

The 2.62 M energy jobs in the US in 2017 are highly diffuse and unevenly distributed across the country. Ninety-seven percent of counties have at least one person employed in the oil and gas industry (including drilling, extraction and distribution-related activities and manufacturing and other support activities sub-sectors). Conversely, renewable jobs tend to be concentrated in just a handful of counties. Hydropower is found in just 396 counties – the most counties of any renewable energy. The number of people employed in each county also substantially varies. While the median number of jobs in the oil and gas industry per county is 48 employees, Harris County, Texas has more jobs in this industry than any other county in the country (125,455 FTEs). It should be noted that Harris County is a clear outlier for energy employment as it has the largest economic output for 8 of the 18 pre-selected energy sub-sectors and is the largest employer in T&D

(9,014), wind generation (1157) and the related construction sector (16,801). The oil and gas industry is the largest employer in 151 counties, while other energy sectors are the largest employer in few counties: coal mining in 12 counties, fossil fuel generation in six, nuclear in five and wind and turbine and generator manufacturing in one county each. County-level energy sector employment statistics are shown in Table S5 of the SI Section 7.

The period from 2002 to 2017 saw a substantial shift in trends for energy employment. Employees of the traditional baseload generation sectors (i.e., hydropower, fossil fuel and nuclear) were present in fewer counties (a decrease of 237, 84 and 3 counties, respectively) and lost a significant number of jobs (61,233, 58,964 and 2043). The non-traditional renewables (i.e., wind, solar, biomass and geothermal) were present in fewer counties in 2017 (a decrease of 42, 118, 132 and 237 counties, respectively), but overall created 11,791 jobs over this period with wind, solar and biomass growing (4806, 5128 and 2312 jobs, respectively) and geothermal losing 237 FTEs.

3.2. US energy economy clusters in the US

Our GM models identified 14 distinct cluster archetypes, with a total of 12 clusters identified in each period (details in Table S5). Almost one in five US counties belonged to an energy cluster at least once, with 345 counties on average being in a cluster in any given year. On average, 78 % counties in a cluster were in an extraction or fossil generation cluster, while only 8 % were associated with nuclear and hydropower clusters and 12 % with a support industry clusters. The only two clusters for a renewable energy source consisted of 29 hydropower counties and only appeared in 2002 (Fig. 2A).

The geographic location of clusters follows expectations for the distribution of energy resources. Coal mining clusters (red shades in Fig. 2) are in the Appalachian (West Virginia, Virginia, Pennsylvania, Ohio, Kentucky and Alabama), Powder River (Wyoming, North Dakota, Montana, Colorado and Utah) and Illinois (Illinois, Indiana and Kentucky) coal basins. These maps (and the maps for 2007 and 2012 in Fig. S4 of SI Section 8) also show the shale gas boom corresponding to a growth in oil and gas drilling clusters (brown shades) as shale plays are explored over time. Counties in the nuclear (green) and fossil fuel (orange) generation clusters have documented electricity generation capacity [57]. All this serves as a check for our clustering algorithm to boost confidence in our algorithm's results.

3.3. Energy employment cluster dynamics from 2002 to 2017

The oil and gas drilling clusters showed the largest growth over our time period, tripling in size by 2012 compared to 2002, as the shale gas revolution led to job growth in the Fayetteville (Arkansas) and

Haynesville (Louisiana and Arkansas), Marcellus and Utica (Pennsylvania, West Virginia, Ohio) and Bakken (North Dakota) shale plays. Most of the newly clustered oil and gas extraction counties, 113 in total from 2007 to 2012, moved from low dependence on energy jobs to the low-intensity oil and gas cluster. However, as the shale gas boom wound down in these counties, many were once again reclassified in the low dependence cluster by 2017.

Besides the shale revolution, other trends in the recent history of the energy sector are evident in the Sankey diagram (Fig. 3). The size of the coal mining and fossil fuel generation clusters fell by 28 counties (a 32 % decrease from its 2002 size) and 13 counties (a 21 % decrease from its 2002 size), respectively. The number of counties in the high and low nuclear clusters fluctuated before stabilizing at 35 counties in 2012. The turbine and generator manufacturing cluster was at its largest in 2017 (6 counties) and the transmission and distribution cluster is the most variable in size as counties move between it and the low dependence cluster.

3.4. Sensitivity and adaptive capacity

In general, counties in any energy employment clusters had a slightly lower RETI score compared to counties in the group with low dependence on energy jobs group (SI Section 9 and Table S7). However, this trend masks substantial variation between clusters. For instance, the coal-related clusters appear to have low RETI scores, unlike those with nuclear- and oil and gas-dominance which have higher scores. Overall, the least resilient county in any energy cluster for 2017 was McDowell, WV (RETI score of -0.75), a county in the high-influence coal mining cluster in all years. This is representative for the coal mining clusters, as seven of the ten least resilient counties in any energy-reliant clusters were associated with coal mining. The highest RETI score for any energy cluster was found in the low-nuclear clustered San Luis Obispo County, CA (RETI score of 1.78). Being classified into the oil and gas sector was also positively correlated with being socio-economically resilient as seven of the top ten most resilient energy clustered counties were associated with it in 2017.

We plotted the cluster-specific cumulative distribution functions of the RETI scores to identify differences in distributions (Fig. 4). Coal mining clusters tend to have lower RETI scores and their median RETI is the lowest among all energy job clusters. We also see differences based on the intensity of reliance on coal mining as the median RETI of the high-coal mining cluster is substantively lower than that of the low-coal cluster. This indicates that being more reliant on coal mining is correlated with decreased resilience. The next least resilient cluster is the high-influence fossil fuel generation cluster. Turbine and generator manufacturing has the highest median RETI score of any energy-reliant cluster while (perhaps surprisingly) the median RETI scores for the oil

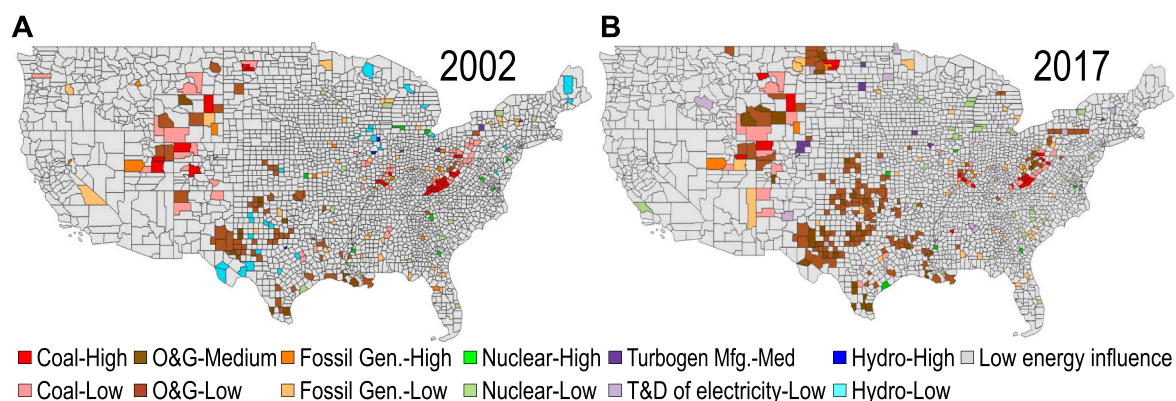


Fig. 2. Clusters based on local energy employment in (A) 2002 and (B) 2017. In SI Section 8, we present the maps for 2007 and 2012 (Fig. S4) and cluster descriptions and counts (Table S6). The group of counties with low dependence on energy jobs—counties that had too few employees to be incorporated into an energy cluster—is the most common in all the studied years (colored in grey).

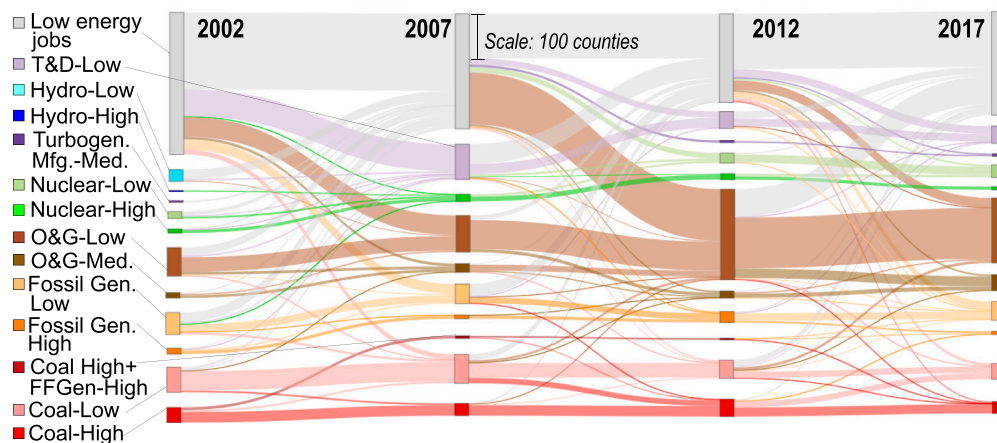


Fig. 3. Evolution of the energy job clusters during our study period. The prominent increase of brown counties from 2007 to 2012 reflects the shale boom. This Sankey diagram shows the 590 counties that are in energy clusters at any point in our analysis. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and gas drilling clusters also rank comparatively high in second (O&G-Low) and third (O&G-High) place.

By quantitatively comparing county RETI scores using a MWW test, we found significant differences between counties. The MWW test results indicate that the coal clusters with high and low influence are significantly less resilient to the transition than other clusters. This supports our qualitative conclusions based on Fig. 4. On the other end of the spectrum, the low intensity oil and gas and turbine and generator manufacturing clusters significantly outperformed five other clusters. However, we did not find significant difference between these clusters with respect to the group with low dependence on energy employment. This set of clusters was followed by the low-intensity nuclear cluster (and the low-dependence cluster) that showed significantly higher resilience than four other clusters. The results from the cluster comparison at national and regional levels can be found in SI Section 10 and Fig. S5 and state-level differences in SI Section 11 and Fig. S6.

4. Discussion

We designed a regional case study in three states (Pennsylvania, Ohio and West Virginia) that have historically relied on energy extraction industries (including the recent Marcellus-Utica shale gas boom) and have faced economic shocks in the past. As part of the ‘Rust Belt’, Ohio and Pennsylvania lost in total about 50,000 manufacturing jobs during the 1980s [58] and West Virginia lost more than 10,000 during the 2007–2009 Great Recession [59]. During the shale revolution, these three states became significant natural gas producers, accounting for 46 % of the nation's shale gas in 2017 [2]. This led to substantial job growth as the six oil and gas sub-sectors created 44,080 jobs in these states between 2007 and 2017 – five times the net loss of jobs in coal mining [1]. Our clustering analysis results reflect this trend as well, as the number of counties in an oil and gas cluster grew from seven to 19 while the coal mining clusters shrank from 30 to 19.

Despite economic growth associated with the shale gas boom, the socio-economic conditions on the ground in these states indicate continued, substantial economic risk during the energy transition. Compared to elsewhere, energy-dependent counties in PA, OH and WV had lower RETI scores in 2017 as the state-aggregated medians rank 25th, 33rd and 41st, respectively, out of the 48 analyzed states. These ranks drop to 30th, 35th and 47th if the comparison includes all counties and not just energy-dependent ones. All three states in this region have low educational attainment and solar resources. West Virginia also has high levels of child poverty and unemployment, low levels of internet connection and wind resources and the lowest number of renewable policy instruments of any state in the US.

These states have each taken different approaches to preparing for the energy transition. The number of renewable policy instruments was one salient differentiator for their RETI in the region with Pennsylvania having 52 instruments (ranked 10th overall), Ohio having a 33 instruments (ranked 20th overall) and West Virginia having no relevant state-level policies (ranked 48th out of 48 overall). Policies that promote the development of renewable resources can create adaptive capacity by boosting local tax bases, diversifying the local economy and improving community services (e.g., infrastructure and education) [60]. It should be further noted that areas with moderate to low renewable resource potential (including parts of these states) can participate in the transition through energy efficiency activities, grid modernization, environmental remediation [61] and manufacturing in the energy sector value chain [62].

In this region, trends in the differences in cluster-median RETI scores followed those of the continental US – with the exception of the oil and gas clusters (see the MWW rank-sum test results for this region in Fig. S5B). This indicates that, in general, counties with energy dependence are less socio-economically resilient than those with few energy jobs, coal mining clustered counties being the most vulnerable (and the only counties with RETI scores of less than -0.38 in any energy cluster) and the low nuclear generation cluster being the least vulnerable (Fig. 5). Critically, unlike for most of the US, counties in the oil and gas clusters in Ohio, Pennsylvania and West Virginia are not as resilient. It appears that the shale revolution has yet to contribute to the region's socio-economic resilience.

The extraction of shale gas boosted the economy of many Ohio, Pennsylvania and West Virginia counties – including places that formerly depended on coal mining. However, oil and gas booms can have mixed economic and social effects. While natural resource dependence is frequently associated with low economic development [63], there typically is a rapid growth in employment in early stages of natural gas well development. However, the employment growth from oil and gas does not translate into rapid growth in employee earnings as the industry is more capital-intensive than labor-intensive [64]. Furthermore, the long-term impacts of these changes depend on the nature of the activities that were affected [65]. The employment growth in oil and gas also affects pre-existing economic activities in an area and its local social dynamics and shifts employment qualification profiles – all of which influences economic resilience [64,66]. Oil and gas development may crowd out labor from other industries with similar skillsets and the jobs that are generated may “leak” out of the county [67,68]. The cost of living may also rise and economic activities (like those based on natural capital) may be displaced.

Economic growth in counties that transitioned from coal mining to

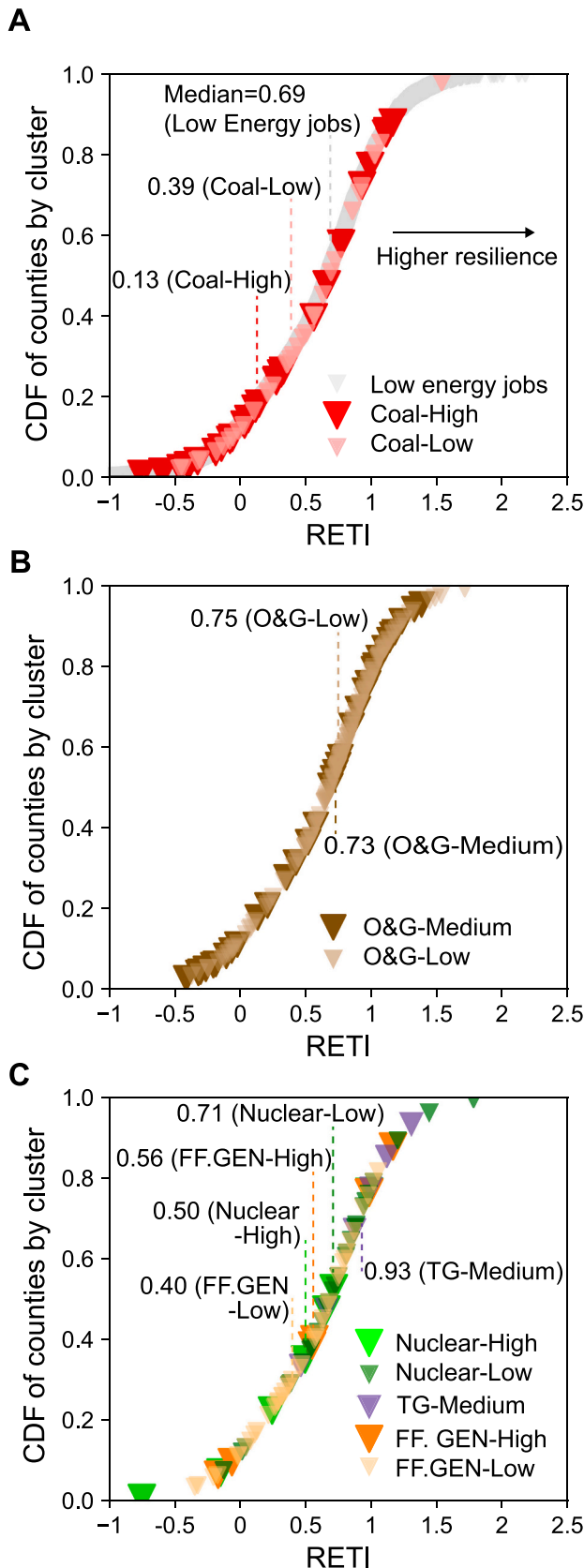


Fig. 4. Cumulative Distribution Functions of county RETI by energy jobs cluster. Differences between groups were quantitatively evaluated using the Mann-Whitney-Wilcoxon rank-sum test (SI Section 10 and Fig. S5A).

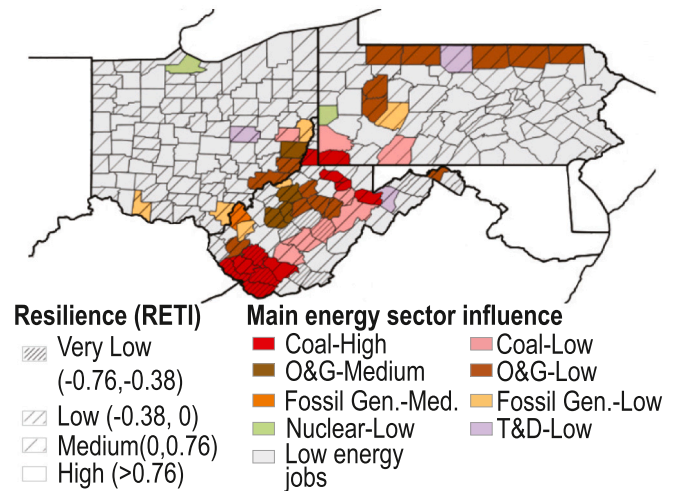


Fig. 5. Resilience and energy dependence cluster map in the Marcellus-Utica case study. The red clusters (i.e., high-intensity coal mining) tend to have denser hatching which indicates a lower resilience. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

oil and gas extraction has not significantly improved socio-economic resilience. This is evidenced by the fact that the three counties that transitioned from the coal mining to the oil and gas extraction clusters still had low RETI scores. Armstrong, Pennsylvania and Upshur, West Virginia had RETI scores well below state medians (0.51 vs 0.68 for Armstrong County and -0.9 vs -0.2 for Upshur County). Belmont County, the county with the largest production of shale gas in Ohio in 2016 [69], was also slightly below the Ohio median RETI (0.58 vs 0.60). In general, most RETI socio-economic variables in Belmont, Upshur and Armstrong counties were behind the region and the country after the shale gas boom (Fig. 6) and either decreased or grew slower than the US median from 2017 to 2020 (SI Section 12 and Table S8). In particular, the performance of these three counties does not appear to substantially differ from counties that continued to be classified in the coal-mining clusters. Greene County, Pennsylvania consistently relied in coal mining for every year in our study period and yet had a higher RETI in 2017 (0.56) than Armstrong and a better trend in most socio-economic indices for the next three-year period. McDowell County, West Virginia had the lowest RETI in the region (-0.75) but is improving significantly faster than the US and the region thanks to its reduction of childhood poverty, education and lack of internet connectivity. This strongly suggests that short-term investments and economic growth from shale gas industries has yet to meaningfully improve socio-economic resilience compared to those counties that did not pursue shale gas.

These results raise questions about the effects of non-renewable industries on county-level resilience – and sustainability. Both resilience and sustainability aim to provide benefits to people under extreme conditions [70] like the distress caused from the losses of fossil-fuel industries in the energy transition. Therefore, the low RETI of oil-and-gas-reliant counties is also a sustainability problem. The framework of weak sustainability lets us address this problem by examining how oil and gas activities create wealth for future generations in the region [71]. According to the Hartwick's rule [72], a county would be (weakly) sustainable if productivity from other forms of capital created (e.g., human capital developed by education, manufactured capital in the form of infrastructure) by the oil and gas industry exceed the loss of natural capital via mineral extraction.

To explore the possibility of weak sustainability enabled by the oil and gas industry, we can examine the sector's investments to improve roads and bridges and the property tax contributions towards education. In Belmont County, the oil and gas industry invested \$62 M to improve

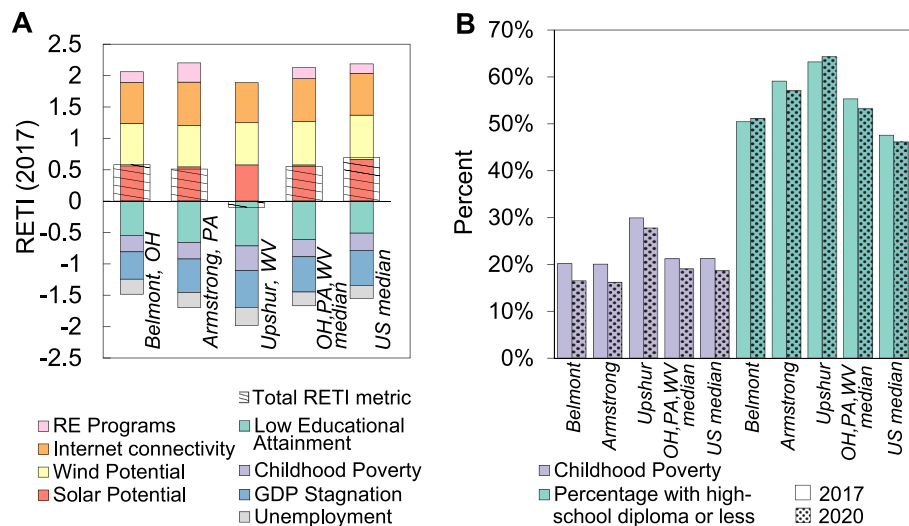


Fig. 6. Components of the RETI in the three counties that migrated from coal to oil and gas clusters. Panel (A) shows the eight normalized variables related to sensitivity (negative) and adaptive capacity (positive). The hatched transparent bar represents the total of the RETI metric that results from adding the adaptive capacity measures (in the positive direction) and subtracting the sensitivity ones. Panel (B) depicts the trends of two socio-economic variables in these counties. The three of them had faster reduction in child poverty than the regional median, but Belmont and Upshur experienced a decline in the educational attainment. These three counties remain below the US median in 2020 in this variable.

93 miles of roads and bridges between 2011 and 2017. However, these improvements are associated with Road Use Maintenance Agreements and are for road segments related to gas well operations [73] with only indirect social benefits. On the other hand, approximately 60 % of collected property taxes (\$16.8 M in between 2011 and 2017) are allocated to education [74]. These investments of tax revenue in education are more consistent with improving sustainability and promoting socio-economic resilience as future wealth in the form of human capital and is commonly considered in comprehensive wealth metrics [16,75] and value creation from education has been considered implicit in future earnings and productivity [76]. Given these facts, not all capital creation activities are guaranteed to produce a more sustainable and resilient society as the value of infrastructure investment depends on its use after the transition while education investments translate directly to future wealth.

Like the extractive sub-sectors, power generation can also help build effective adaptive capacity in the region by investing in other types of reproducible capital. These forms of capital creation can increase socio-economic resilience depending on the level of alignment with the transition. Two nuclear-clustered counties, Ottawa County, Ohio and Beaver County, Pennsylvania (RETI scores of 0.89 and 0.85, respectively), demonstrate how this can be done as public and private stakeholders leverage the nuclear industry to further create capital suitable for a decarbonized future. Ottawa County is home to a research, development and deployment project on nuclear-based hydrogen financed by the US Department of Energy [77]. A Beaver County power utility is forming a long-term partnership to power a large data center [78]. These investments stand in stark contrast to investments made in Adams County, Ohio. In 2011, an electric utility opened a \$4.5 M training center in Adams County for future fossil generation employees [79] requiring millions of dollars to be invested in training equipment to produce human capital. This investment failed to contribute to preparing the county for the transition as it had the second lowest RETI in Ohio in 2017 (−0.21) and continued to be in particular need of human capital [22]. The financial and human capital created by that investment was stranded when the local coal-fired power plants, Killen and Stuart, closed in 2018 [80]. Its construction increased the Adams County's exposure to the energy transition – instead of increasing its adaptive capacity – as it attracted more people and more infrastructure to the fossil generation sub-sector. The coal plant closures were also a substantial blow to the County's tax revenues, as utilities are the sole industry in the state that is subject to the tangible personal property tax [81]. This unique tax structure could have intensified investment in technology rather than in human capital, exacerbating the reliance on

capital-intensive industries [82].

Renewable energy manufacturing can also play a critical role in improving socio-economic resilience during the transition in the region. Manufacturing has historically been a provider of high-wage jobs, commercial innovation and a contributor to environmental sustainability [83]. A manufacturing-focused strategy can also take advantage of the fact that the sectors that produce services or products that are a net benefit for the environment (e.g., low-carbon energy) are more intense in manufacturing jobs compared to the economy as a whole (26 % vs. 9 %) [84]. Current energy manufacturing capacities do not reflect the region's manufacturing Rust Belt past, as only one county in the region (Knox County, Ohio) fell into a relevant manufacturing for energy cluster, the turbine and generator manufacturing cluster. Development of heavy industries can link potential elements from this manufacturing past with the energy transition. This would allow manufacturing to serve as a bridge industry during decarbonization given similarities in labor skillsets between power plant and mineral extraction employees and maintenance and mechanics [81] and the opportunity to reconstruct labor and cultural identities [10]. However, developing policies to leverage these features of manufacturing industries will require future work to better understand underlying assumptions.

Community-transition support complements policies on diversification, job creation and protection of workers as they target the same overarching goal of defending the living standards of individuals in vulnerable communities at relatively small costs [61]. Several community-oriented programs have already been implemented in the region to potentially address socio-economic vulnerability and shape the regional post-transition economy. One example of this is the Appalachian Regional Commission's Partnerships for Opportunity and Workforce and Economic Revitalization (POWER) initiative that supports shrinking coal communities. This initiative coordinates efforts around the transition while embracing the region's sense of identity in energy and manufacturing activities. Since 2015, the POWER initiative has invested \$316 M in activities like training, environmental remediation, broadband development and entrepreneurship. These interventions are well situated to address the three dimensions of vulnerability and are supported by just transition literature findings [85,86].

5. Conclusions

We developed a methodological framework that incorporates county reliance on energy employment into a vulnerability assessment and use this framework to characterize the ability of each county in the continental US to adapt to a low-carbon energy future and the relationship

between different energy-related sub-sectors and socio-economic resilience. We used ML to identify clusters of counties that are similarly exposed to the decline of fossil fuels given the fraction of jobs that rely on different energy extraction and utilization activities. The most frequent energy clusters were related to fossil energy extraction, while no clusters were defined by renewable energy except for hydropower (and only in the first year of our analysis). We further found significant differences in cluster-level socio-economic resilience as our results showed that coal mining-reliant counties were significantly more vulnerable than counties in other clusters. We also found that while oil and gas clusters had relatively high resilience across the country, this was not the case for oil and gas counties in the Marcellus-Utica shale plays.

From our analysis of oil and gas-reliant counties in the Marcellus-Utica region, we do not find evidence that the shale expansion helped prepare counties for the transition to a low-carbon future. In particular, counties that shifted their dependence on coal mining to rely on shale gas do not show improvements in our resilience metrics compared to those that did not undergo this shift away from coal. Our results further the arguments that metrics of economic output need to be adjusted and scrutinized before being interpreted as indicating improvements to the welfare of society [16,76]. The low resilience in counties that depend on energy extraction and the lack of evidence that RETI grew during (or after) the shale gas boom suggests that current transfers from non-renewable industries to non-financial types of capital may not enhance sustainability and resilience – without meaningful policy interventions. Kelsey et al. [87] recommends economic policies to better collect the benefits from extraction-oriented economic booms including recognizing the temporal nature of the growth and leveraging transfers to create long-lasting local capabilities. Interventions that are designed to create non-financial capital from fossil industries should explicitly contribute to inclusive wealth measures (e.g., human, social and environmental capital) outside of the fossil-fuel sector to strengthen communities and their resilience more effectively.

Interventions that serve non-renewable industries without creating other types of capital should be scrutinized to avoid the creation of stranded assets. Accounting for functional depreciation, in which an asset loses value due to technological obsolescence, is required to measure intergenerational well-being as part of a comprehensive wealth criterion [88]. It can determine if an intervention builds reproducible capital or capital assets that will become stranded after the transition. Policies and interventions that incentivize the natural capital consumption, even perhaps beyond environmentally-tolerable losses [89,90], can still be weakly sustainable if they support the transition by creating human, social and infrastructure capital that is valuable for a low-carbon economy.

Our RETI framework meaningfully integrates exposure due to the presence of a fossil energy workforce with relevant measures of resilience during the energy transition. A vulnerability assessment based on our RETI metric can be used and improved upon to evaluate the effects from interventions and industrial shifts on community resilience during the transition. The RETI metric does not attempt to be a projection of future jobs in a county, instead it reflects relative county vulnerability and economic well-being. Tracking this metric across time can therefore be useful in identifying lasting effects from local events in energy sectors. A multi-decadal analysis of the RETI can uncover long-term community impacts of “bridge” fuels (i.e., natural gas), policy interventions, investments and industrial trends. Assessments with finer spatial resolution (e.g., zip code-level) can be used to capture impacts with a focus on vulnerable populations within counties. Besides refining the framework in spatial or temporal scales, further work with the RETI can refine its design and variable selection to potentially allow it to measure other types of economic activity. However, our objective is not to design a comprehensive metric of resilience, but a meaningful one that captures significant elements of community sensitivity and adaptive capacity during the energy transition. Performing a thorough literature review

and analyses of interdependence (e.g., correlation analysis between RETI components) can highlight any future needs to improve the RETI design. The use of econometric approaches and comparative analyses with other US coal mining or shale gas extraction regions can further explore the relationship between energy extraction and the growth of community resilience and sustainability. Furthermore, incorporating potential cultural, labor and infrastructure indicators and the state of produced capital for manufacturing and emerging energy industries (e.g., energy efficiency, digital services for energy and infrastructure and energy storage) can potentially enrich our RETI regional analysis and explore other sources of adaptive capacity.

Symbols

<i>E</i>	Employment [FTE]
<i>e</i>	Normalized employment [–]
<i>RETI</i>	Resilience during the Energy Transition Index [–]
<i>s</i>	Average Direct Normal Irradiance [W/m ²]
<i>w</i>	Average wind speed at 100 m [m/s]
<i>p</i>	Number of pro-renewable policy programs in a county [#]
<i>i</i>	Percentage of households with internet access [%]
<i>h</i>	Percent of children poverty [%]
<i>g</i>	Annual county GDP growth [%/yr]
<i>d</i>	Percent of population over 25 years without any college education [%]
<i>u</i>	Unemployment rate of labor force 16 years or above [%]

Subscripts

<i>i</i>	Industry
<i>c</i>	County
<i>t</i>	Period

Superscripts

‘	Normalized variable
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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

Code and most of the data is available upon request to the authors. Employment data however is proprietary and cannot be shared.

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Appendix A. Supplementary documentation

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.erss.2023.103099>.

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