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Assessing Compounding Risks Across Multiple Systems and Sectors: A Socio-Environmental Systems Risk-Triage Approach

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To this end, the Joint Program brings together an interdisciplinary group from two established MIT research centers: the **Center for Global Change Science (CGCS)** and the **Center for Energy and Environmental Policy Research (CEEPR)**. These two centers—along with collaborators from the Marine Biology Laboratory (MBL) at Woods Hole and short- and long-term visitors—provide the united vision needed to solve global challenges.

At the heart of much of the program's work lies MIT's Integrated Global System Model. Through this integrated model, the program seeks to discover new interactions among natural and human climate system components; objectively assess uncertainty in economic and climate projections; critically and quantitatively analyze environmental management and policy proposals; understand complex connections among the many forces that will shape our future; and improve methods to model, monitor and verify greenhouse gas emissions and climatic impacts.

This report is intended to communicate research results and improve public understanding of global environment and energy challenges, thereby contributing to informed debate about climate change and the economic and social implications of policy alternatives.

—Ronald G. Prinn,
Joint Program Director

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Abstract: Physical and societal risks across the natural, managed, and built environments are becoming increasingly complex, multi-faceted, and compounding. Such risks stem from socio-economic and environmental stresses that co-evolve and force tipping points and instabilities. Robust decision-making necessitates extensive analyses and model assessments for insights toward solutions. However, these exercises are consumptive in terms of computational and investigative resources. In practical terms, such exercises cannot be performed extensively – but selectively in terms of priority and scale. Therefore, an efficient analysis platform is needed through which the variety of multi-systems/sector observational and simulated data can be readily incorporated, combined, diagnosed, visualized, and in doing so, identifies "hotspots" of salient compounding threats. In view of this, we have constructed a "triage-based" visualization and data-sharing platform – the Socio-Environmental Systems Risk Triage (SESRT) – that brings together data across socio-environmental systems, economics, demographics, health, biodiversity, and infrastructure. Through the SESRT website, users can display risk indices that result from weighted combinations of risk metrics they can select. Currently, these risk metrics include land-, water-, and energy systems, biodiversity, as well as demographics, environmental equity, and transportation networks. We highlight the utility of the SESRT platform through several demonstrative analyses over the United States from the national to county level. The SESRT is an open-science tool and available to the community-at-large. We will continue to develop it with an open, accessible, and interactive approach, including academics, researchers, industry, and the general public.

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1. Introduction

Climate and our natural as well as managed environments are changing. Society is growing and its aging infrastructure to provide reliable energy, water, and transportation systems is increasingly strained and challenged by needed expansion, upgrades, and modernization. Further, the gobal economy, energy systems, and supply chains are faced with the challenge of transformational changes at a global scale. Simply put, the world is facing increasing and interwoven physical and transitional risks. In order to confront these challenges, the scientific community, stakeholders, and citizen scientists must view the world as complex, interwoven networks that co-evolve and are increasingly inter-connected. Multi-Sector Dynamics (MSD, e.g. **Figure 1**) explores interactions and interdependencies among human and natural systems and how these systems co-evolve in response to short-term shocks and long-term influences and stresses (e.g. Reed *et al.*, 2022). For example, economic growth might put a pressure on public services and squeeze out low-income households (e.g. Frank, 2009), carbon policies can lead to different distributional impacts on households (e.g. Garcia-Muroz *et al.*, 2022), and failed economies lead to widespread poverty, unemployment, tax base decline, and transform demographic geographies (e.g. Hochstenbach and Musterd, 2018). Under a changing global environment, weather may become more extreme, leading to increasing extreme events, such as droughts and floods (e.g., Stott *et al.*, 2016). Efforts to curb emissions will affect air pollution, but can also exert unintended and unequal stress on communities (e.g. Kiesecker, 2019). Similarly, water pollution, or efforts to reduce it, while having clear health benefits can have unequal social and economic impacts (e.g., Mueller and Gasteyer, 2021). As the world economy changes, perhaps turning away from fossil fuels to toward other energy resources, resource use could change drastically leading to regional increases and declines in related industries. A growing global population that is becoming wealthier will put greater pressure on energy, land, and water resources.

In this vein, among the major challenges that Federal and State agencies face in addressing and identifying these problems lies in the difficulty of combining data to assess hazards, quantify overall risk, and set priorities. Currently, much of the needed data is disaggregated across multiple agencies, universities, and research groups, and presented at different geographical scales in varying formats. Finding and accessing all these data

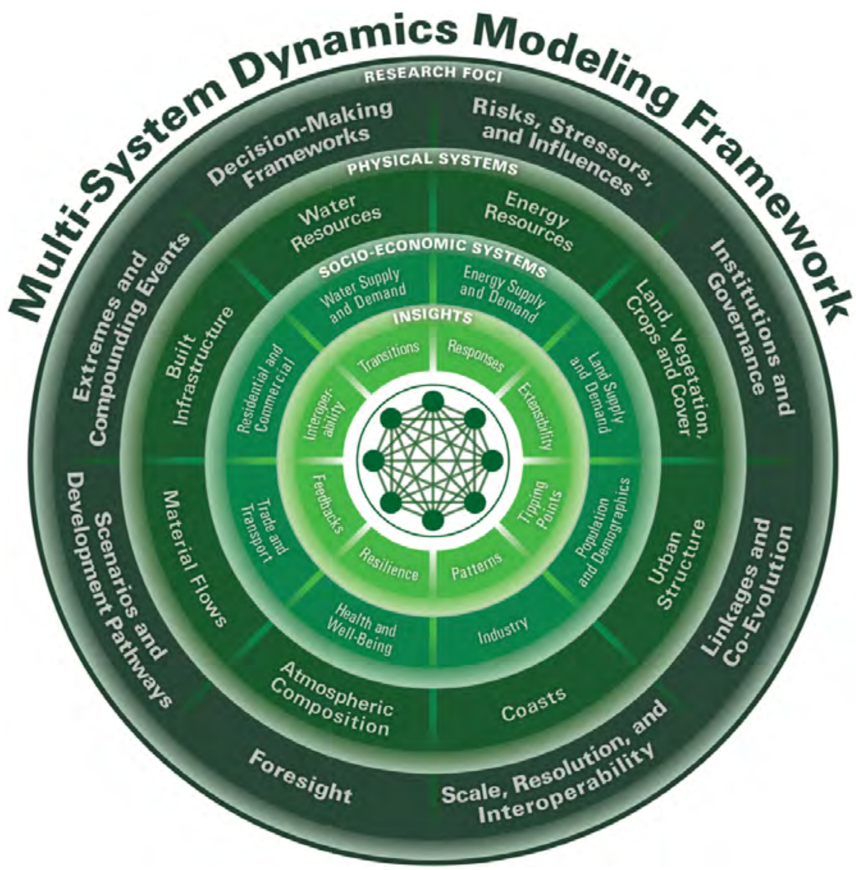

Figure 1. Schematic representation of the Multi-Sector Dynamic framework that recognizes the co-evolving nature of socio-economic and physical systems. These systems must be considered as connected to gain insights into the various landscapes of vulnerabilities, compounding risks, and environmental instabilities and inequalities.

are also a challenge in itself. More importantly, combining these data and creating metrics to address "overall risk" is unintuitive. On a more granular level, communities around the world will face multiple stressors over the coming decades. The vulnerability or resilience of communities—their ability to successfully cope with stressors—varies. Poorer communities have fewer financial resources on which to draw, and minority communities often do not receive the attention or aid of other communities. Communities with many elderlies or children have a larger proportion of more dependent persons. The overall health of a community and access to health care also results in varying ability to cope with stressors, such as exposure to heat or pollution. Gathering data and projections necessary to understand environmental change and a community's vulnerabilities is itself a significant undertaking. Recruiting experts, evaluating available data and projections, and determining vulnerable infrastructure, populations, and economic activity even at a very low level can require hundreds of thousands of dollars, if not many millions. With this consideration in mind – an efficient, low-cost screening level assessment that can identify "hot-spots" and allow a user to prioritize where resources and efforts can be most appropriately deployed would be valuable.

This paper describes a collection of data, constructed metrics, and an interactive, visualization platform that allows citizen, scientists, communities, states, and the Federal government to identify particularly vulnerable regions, populations, infrastructure, and resources. This web-based platform can be used to prioritize efforts in vulnerable regions to increase resilience against the identified potential stresses. Overall, we refer to this as a "risk-triage" approach, with "triage" aligning with its definitional context of "...assigning of priority order to projects on the basis of where funds and other resources can be best used, are most needed, or are most likely to achieve success" (Marion Webster Dictionary, 2021). Our goal is to characterize how the risk of various stressors co-exist, compile them in an easy to use and flexible fashion, and identify how the aggregate risk landscape changes when individual risks are combined. From this screening-level assessment, "hotspots" of risk can be identified that point to deeper diagnoses of risks at a more granular and detailed level, and these steps should lead to action to improve resilience. Identifying the most vulnerable region provides an opportunity to intervene before there are serious effects. In the section that follows, we discuss our conceptual foundation and methodology that combines data and provide a link to a website that implements the conceptual model. We developed the platform to have flexibility to change or add to the various metrics in response to feedback from the research community and more importantly, government and private stakeholders as well as citizen scientists. Such feedback may point to areas where new data or projection capability may be needed. The current implementation presented herein focuses on assessing current vulnerabilities and current stressors, with later versions indented to project potential changes in stressors. To highlight the current capabilities of the platform, we then provide some examples and demonstrative analyses over the United States from the national to county level. Summary and closing remarks describe our continued efforts to expand the platform's capabilities.

2. Methodology

2.1 Conceptual Considerations

Stakeholders, legislators, decision-makers, as well as the community-at-large face increasingly complex exposures and compounding effects from co-evolving environmental, economic, and societal pressures. A number of online data, visualization, and analysis platforms are currently available to the community-at-large for exploring a wide range of climate, social, and environmental hazards (e.g., Pickard *et al.*, 2015; U.S. EPA, 2019, 2020; Temper *et al.*, 2015; Iturbide *et al.*, 2020; NOAA NCEI, 2022; Zuzak *et al.*, 2021). All these platforms carry unique perspectives and strengths, yet what they lack is the ability to combine and weight user-selected metrics to quantitatively assess compounding hazards. The extent of data that is accessible to visualize and quantify these pressures and stresses is substantial (e.g. see Appendix A). Yet in many cases, such data are neither provided nor processed in a suitable form such that they can be readily combined. Flexible and user-specified combinatory diagnostics such as these would provide valuable perspectives and identify salient priorities and vulnerabilities for investment and action. To use an example as conceptual motivation, imagine a situation in which a particular region of interest (e.g. nation, state, or county) is prone to high flood risk. Any flood risk metric by itself would identify areas at high risk, however, infrastructure, demographics, and poverty could make some areas less able to withstand a flood and less resilient to recover than others. However, compiling and combining all the necessary data to make a quantitative assessment with all these combined factors (and potentially weighted according to a decision-maker's judgement) is not readily available. A tool to combine compounding factors that identify the most risk-prone areas is valuable and insightful as a triage-response assessment. Similarly, communities might use such a tool identify their vulnerabilities with respect to an array of stressors and their combinations.

We believe that under the conception of a "risk-triage" capability, a visualization platform should include metrics of stressors, risks, vulnerabilities, and resilience across socio-economic, climate, water, land, energy, demographic, and infrastructure sectors, and that any metric should characterize the conditions and resources needed to cope with both gradual and sudden stressors. For example, the tool should encompass a gradual event such as economic decline from the fading of a communities' dominant industry, or a sudden, extreme event like a large flood. The platform likewise needs to be flexible: it must encompass and have the ability to quantitatively combine and visualize different types of metrics. The tool should include metrics that indicate current and the potential of future stresses. However, it cannot be expected to provide precise predictors of what and when something will happen, but rather, the tool can convey a quantitative description of multiple risks that can be viewed individually and in any desired combination – so that the impact of compounding effects can be assessed under current conditions and future pathways. These futures could be a result of plausible (and uncertain) trajectories of climate, weather extremes, socio-economic growth, land cover/use, land and ecosystem productivity, water resources, and air quality to name a few.

There are numerous data bases available from various Federal, non-profit, and open-science research institutions (see Appendix A) that provide a wide range of social, economic, and environmental variables (e.g., Pickard *et al.*, 2015; U.S. EPA, 2019, 2020; Temper *et al.*, 2015; Iturbide *et al.*, 2020; NOAA NCEI, 2022; Zuzak *et al.*, 2021). Depending on the data structure, content, and granularity, they are provided in various downloadable forms and formats. We have relied on these data to populate a "one-stop" collection of data to serve as a Socio-Environmental Systems Risk Triage (SESRT) platform (URL – mst.mit.edu). In doing so, we also use these data to synthesize a collection of risk metrics that allow for the combinatory diagnostics, which is detailed in the next section. Overall, the principles by which the SESRT has been and continues to developed are (1) describe "hotspots" and prioritize further action and deeper inspection of risk or threats rather than just report data, and (2) strive for comprehensiveness, as data prepared by various agencies and institutes each have a relatively narrowed auspice (3) create normalized risk metrics that allow for user-defined, combinatory analyses across risks and vulnerabilities. The subsequent compounding-risk metrics offer an intuitive and collective ability to identify regions most in need of attention. We allow users to aggregate or view a single metric given their focus and interests. As such, a user of the platform could be able to identify, for example, the "top-10" riskiest locations/regions with the most vulnerable populations, resources, and infrastructure across all potential stressors, allowing for specific risks and weights within those categories. Or one could create a more focused assessment, like the one described above, of infrastructure most at risk from extreme flooding with highly vulnerable populations. Some examples of these are provided in Section 3 to highlight a range of potential applications. As previously discussed, in the context of "triage", the SESRT platform is intended to provide a rapid assessment, allowing reasonable prioritization, on the basis that an efficient "hotspot" analysis is more effective than exhaustive, extensive deep-dive assessments that are time-and-resource consuming. In fact, the intent of the "risk-triage" approach is to identify more specific targets for these deep-dive assessments.

2.2 Risk Metrics and Combinatory Analyses

The initial focus of our data collection has been over the United States at the county-level scale. We have and continue to collect publicly available data from the community-at-large that has resulted in a metadata collection (described in Appendix A) of currently over 100 variables that quantify a variety of fluxes, flows, states, and conditions across various landscapes of socio-environmental sectors, demographics, and public opinion. In view of the conceptual approach and methodology (Section 2), we have selected a subset of these variables that serve as the basis for the combinatory risk metrics analysis and visualization. As such, these metrics are "normalized" such that a user can chose various combinations to assess the extent of their co-existence – and to be able to gauge the "severity" in such a way that provides a quantitative basis for identifying "hotspots" of risk. The procedure to construct these metrics is described below.

Our approach to construct these combinatory risk metrics is flexible and extensible by design. Conceivably, any variable from the main topical areas described above can be represented and selected. Initially, we have selected variables from the following topical areas: water; land; climate; economy; energy; health; biodiversity, and demographics. From these, we have further refined and constructed 17 variables for use as combinatory risk metrics. This collection of metrics will continue to be expanded under the SESRT mission to provide a comprehensive assessment of compounding and co-evolving risks. The current set of risk metrics are presented in **Table 1**.

A primary consideration to the construction of an aggregate metric is that each of the risk metrics described above carries inconsistent units, and therefore in their constructed form, any combinatory, comparative, and/or prioritizing diagnostics are untenable. To provide a capacity for these metrics to be combined quantitatively that assures numerical consistency, there are two possible procedures that could be exercised. The first option would be to numerically recast all these metrics under a common-scale categorization of "risk" (e.g., Strzepek *et al.*, 2021; Messer *et al.*, 2014). This scale could be as straightforward as judging each variable under binned categories of "none", "low", "moderate", "severe", and "extreme" risk, or assigning a numerical value for each category or severity of risk (i.e., "none" = 1, "low" = 2, "moderate" = 3, "severe" = 4, and "extreme" = 5). The advantage of this approach is that it preserves the absolute nature of risk, and when combining all the metrics of interest, the resultant metric would highlight all areas "at risk" that have compounded accordingly. The difficulty of this approach is that the rescaling of the raw values according

Table 1. Description and data-source information for the risk metrics that have been constructed for the combinatory analyses.

Variable	Description	Data Sources
Exposure to airborne particulate matter	Annual $PM_{2.5}$ concentration data in the U.S., 1 km resolution, weighted by population and summed to the county (ug/m^3).	$PM_{2.5}$ Data: Gridded concentrations of fine particulate matter ($PM_{2.5}$) from Di *et al.* (2019 & 2021) Land area data: https://sedac.ciesin.columbia.edu/data/set/gpw-v4-land-water-area-rev11/data-download Population density: https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-adjusted-to-2015-unwpp-country-totals-rev11 (CIESIN, 2018) Statistic constructed from 2015 data.
Water Stress	Approximate proportion of the available water used. Estimated as withdrawal divided by total runoff.	Runoff: derived from ERA5 reanalysis Water withdrawal: USGS (https://water.usgs.gov/watuse/data), includes both surface and groundwater withdrawals to determine total freshwater withdrawals. Value for combinatory metric is the average of 2010 and 2015 estimates.
Water Quality	EPA Water Quality Index	EPA Water Quality Index Lower values represent better quality and higher values represent worse quality The EPA created the Water Quality Index from 6 data sources: the WATERS program database, Estimated Use of Water in the United States, the National Atmospheric Deposition Program, the Drought Monitor Network, the National Contaminant Occurrence Database, and the Safe Drinking Water Information System. https://edg.epa.gov/EPADataCommons/public/ORD/CPHEA/EQI_2006_2010/
Flood Risk	First Street Foundation county-level flood risk factor	The county's value is based on the average value across all land parcels that have a flood risk factor value between 2 and 10 (any value lower than 2 is not included). Data available at: https://registry.opendata.aws/fsf-flood-risk/
Highly Erodible Cropland	Cropland that can erode at excessive rates. (From USDA assessment - soils with an erodibility index of eight or more.)	The data are from the USDA National Resources Conservation Service, RCA Report website: www.nrcs.usda.gov/wps/portal/nrcs/detail/?cid=stelprdb1187041 Thematic maps at: https://www.nrcs.usda.gov/Internet/NRCS_RCA/maps/m14598hel17.png Original shapefiles from Tcheuko, Lucas - FPAC-NRCS, Beltsville, MD (Lucas.Tcheuko@usda.gov)
Land disturbance	EPA Land Quality Index, represents five disturbance factors: agriculture, pesticides, facilities, radon, and mining activity.	The index combines data from the 2007 Census of Agriculture, 2009 National Pesticide Use Database, EPA Geospatial Data 12 Download Service, Map of Radon Zones, and Mine Safety and Health Administration. The Land Quality Index is 1 of 5 Environmental Quality Indices by the EPA. Data Downloaded from https://edg.epa.gov/EPADataCommons/public/ORD/CPHEA/EQI_2006_2010
Temperature stress	Temperature of the hottest month out of all months	Surface-air temperature from reanalysis (1980-2019). See Appendix A for further details on reanalysis data.
Fossil fuel employment	Fraction of population employed in fossil fuel industry	The 2020 U.S. Energy & Employment Report by the National Association of State Energy Officials, the Energy Futures Initiative, and the BW Research Partnership, includes job data for electric power generation, transmission, distribution & storage, fuels, energy efficiency, and motor vehicles
Energy expenditure	Expenditures in all energy sectors given as a fraction of GDP	State Energy Data System (SEDS) is the source of the U.S. Energy Information Administration's (EIA) comprehensive state energy statistics.
Endangered species	Metric is the number of species, includes only plants and fungi in the calculation	An international network and data infrastructure funded by the world's governments and aimed at providing anyone, anywhere, open access to data about all types of life on Earth.GBIF.org. The GBIF occurrence download is https://doi.org/10.15468/dl.gew2z6
Wildfire risk	Based on data for mean burn probability (BP)	https://wildfirerisk.org/download
Population under 18	Fraction of population under the age of 18	The U.S. Census Bureau - https://api.census.gov/data/2016/acs/acs5/variables.html
Population over 65	Fraction of population over the age of 65	The U.S. Census Bureau (see link above)
Nonwhite population	Fraction of population nonwhite	The U.S. Census Bureau (see link above)
Population below poverty level	Fraction of population with annual household income below poverty level	The U.S. Census Bureau (see link above)
Unemployment rate	Labor force unemployed	The U.S. Census Bureau - https://www.bls.gov/lau
Homelessness	# of people experiencing homelessness per 10,000 people in 2019. Obtained by dividing the US Housing and Urban Development people experiencing homelessness by the Census Bureau's population counts.	The U.S. Department of Housing and Urban Development's Office of Policy Development and Research (PD&R) https://www.huduser.gov/portal/datasets/ahar/2020-ahar-part-1-pit-estimates-of-homelessness-in-the-us.html

to a common risk scale, that can be combined under user-specified configurations, would be prone to subjective judgement and could lead to distortions of one or more metrics over others. In addition, the process by which each variable is cast into a generic risk scale would be exhaustive and require extensive, expert judgement. A second option, which we have adopted for our initial platform development, is to normalize the metric by ranking their values across any pooled sample of the data. This is an efficient and objective means by which to recast the data. It also aligns with our "triage" methodology, which is to identify high-priority regions. There are options by which to normalize and rank a pooled set of raw data values as well as other approaches that include variance scaling (e.g., Strzepek *et al.* 2021). Considering the intent of the SESRT platform to provide a prioritization of risk, we have taken a percentile ranking approach. As such, for any selected pooling of data (in this case, county-level data pooled across the United States), the following conversion is made. Given the raw value of the data, V_r, we construct a percentile ranking value V_p, for each county (c) value using the expression:

$$V_{p,c} = 100 \cdot \frac{V_{r,c} - \min(V_r)}{\max(V_r) - \min(V_r)}.$$

The minimum (min) and maximum (max) values are obtained from the pooled county-level data collection across the United States or for a particular state (as determined by the user). The values of V_p ranges from 0 to 100 and is unitless, with a value of 0 indicating that the corresponding region has the lowest risk relative to all the other regions across the pooled data, and a value of 100 indicating the highest relative risk.

As previously noted, the intent of the SESRT is to provide the capability to perform user-specified, combinatory analyses and visualization. The use of composite metrics and analyses has been documented and used extensively to explore the complexity and inter-dependencies of various environmental issues (e.g., Saisana and Tarantola 2005; and Greco *et al.*, 2019) The main issues are the choice weighting and aggregation methods across metrics, indicators, and/or variates that are of interest. Among the two more widely used approaches to determining weights (e.g., Sharpe and Andrews, 2012), "explicit" methods consist of evaluating surveys of responses from expert judgement using a Budget Allocation Process or an Analytic Hierarchy Process. The alternative and more objective approaches evaluate the relative importance of indicators based on data compression analyses. Various statistical methods such as Principal Component Analysis (PCA) or Factor Analysis (FA) can be applied for this purpose (e.g., Ram, 1982). These methods place a higher weight on "orthogonal" modes of variability that describe the maximum portion of aggregate variance, and thus a subset of metrics can have more importance in the final weighting. More recently approaches based on artificial intelligence models have been used for this purpose (e.g., Paulvannan Kanmani, *et al.* 2020; Jimenez-Fernandez *et al.*, 2022). However, considering the intent of our platform to provide a flexible, user-inspired tool to explore multiple combinations of physical and transition risks, the debatable issue to the approaches above is that the portion of explained variance does not necessarily directly correspond to the highest value or importance of any metric, and an exhaustive set of expert judgements that span all possible combinations of our collected metrics is elusive. Given this, a final option is to give the user the choice of weights and aggregate the resultant metric accordingly. A wide variety of aggregation methods are used to combine indicators once their relative importance has been chosen. The most common is linear aggregation, though more complex non-compensatory methods are also possible (e.g., Greco *et al.* 2019). We have initially adopted a linear aggregation, and therefore at the user's discretion, any combination of these normalized risk metrics can be combined, at various selected weights – such that the resulting aggregate risk metric V_a based on a total of N normalized metrics combined, described by:

$$V_a = \frac{\sum_{i=1}^{N} W_i V_{p,i}}{\sum_{i=1}^{N} W_i}.$$

Where the assigned weight, W_i, for each individual normalized risk metric ($V_{p,i}$) selected by the user is a constant value (from 0.1 to 1) across all counties. From this procedure, the SESRT platform also constructs a distribution of the resultant data that is displayed. In the section that follows, we provide examples of how this procedure can be used to assess a variety of combinatory, socio-environmental assessments and research applications.

3. Application and Assessment Examples

3.1 National Level Screening

One visual example of the SESRT platform's capabilities is the ability to efficiently indicate where environmental risks compound (**Figure 2**). In this demonstration, the current risks to land disturbances, water availability and quality, as well as exposure to poor air quality can be displayed individually (top panels of Figure 2a), and prominent hotspot regions that face higher levels of each of these separate risks can be discerned (orange/red shaded areas). In viewing these as separate mappings, it is not readily apparent to what degree the more severe areas of these individual environmental risks co-exist and potentially compound. Through the ability of the SESRT platform to combine all four metrics (Figure 2b – all with equal weighting), the landscape of the relative compounding risks is more clearly discernable, with the more prominent visible "hotspots" located across California, the upper and lower Mississippi basin, the Ohio River basin, Texas, the Southeast as well as Mid-Atlantic states.

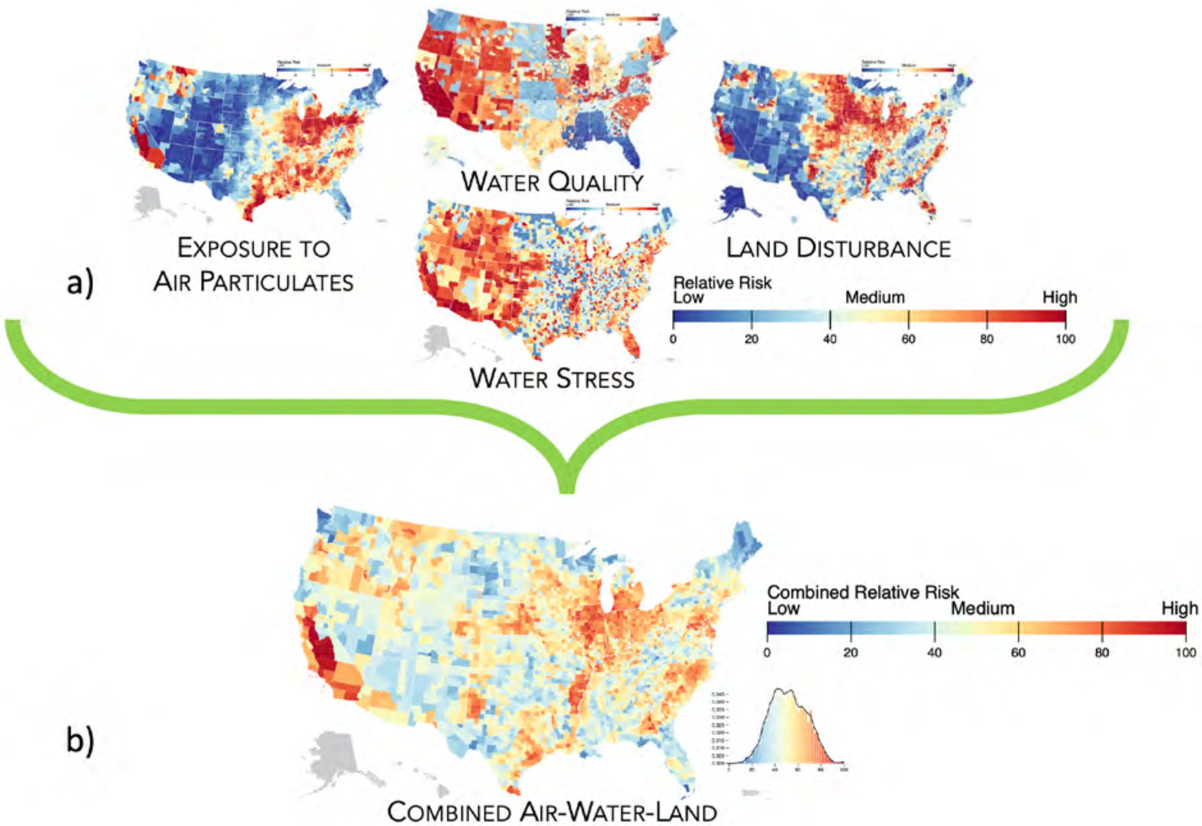

Figure 2. Shown is an example of the combinatory metric analysis provided by the risk-triage framework. In the top panel a), the maps show the results for each metric of exposure to air particulates, water stress, water quality, and land disturbance. In the bottom panel b), the result of the four metrics, combined with equal weighting, is shown. In all panels, the risk metric is unitless and is the result of the normalization procedure (described in Section 2.2). Shades of orange and red indicate the counties with the highest relative risk, while shades of blue indicate the lowest relative degree of risk.

These hotspot areas may all be exacerbated by human-forced changes in climate, extreme events, land use, as well as water and energy demands. Future electricity demand is driven by socio-economic factors (e.g., GDP growth, population growth, technology costs and resulting electricity prices) as well environmental factors, particularly temperature, as driven by climate change, which drives demand for heating and cooling (e.g., Auffhammer *et al.*, 2017; Van Ruijven *et al.*, 2019). The highest density and connections of highest-voltage transmission lines are particularly concentrated in the hotspots of the compounding air-land-water risks across the Central U.S. (orange overlay lines in **Figure 3a** denote Level 3 transmission lines >= 345kV). Concurrently, regions of the nation with the largest portion of employment in the fossil fuel industry, along with high levels of poverty and unemployment flank the lower portions of the Mississippi River (**Figure 3b**). National and global actions to reduce greenhouse emissions could limit risks to land, water, and air quality in the upper basin, but at the same time impacts on the fossil fuel industry could have significant employment impacts in the lower Basin where poverty and unemployment are already disproportionate. Further, climate-related extremes (e.g., droughts, floods, and events that damage transportation infrastructure) can adversely affect the flow of goods along the country's major river route (Figure 3b, the heavy blue line along the Mississippi river). Such disruptions would impact upstream and downstream regions in multiple respects that include energy supplies, agricultural products and inputs, as well as manufactured and raw materials, and all these would have follow-on impacts in other parts of the transportation network, industrial sectors, agriculture and land use, as well as the energy sector. All of these highlight the potential locations of and connections between contrasting regional effects of a low-carbon energy transition.

The co-existence of these interconnected risks in the example above provides motivation, location, and guidance for deeper-dive studies on human-natural system interactions; grid resiliency; and transportation infrastructure. To study these in more detail requires models of greater sophistication and large computational expense – but the presented triaging analyses identifies areas for targeted study, and in doing so reduces the need for exhaustive model simulations and analyses. There are, of course, many other combinations and overlays of compounding risks that can

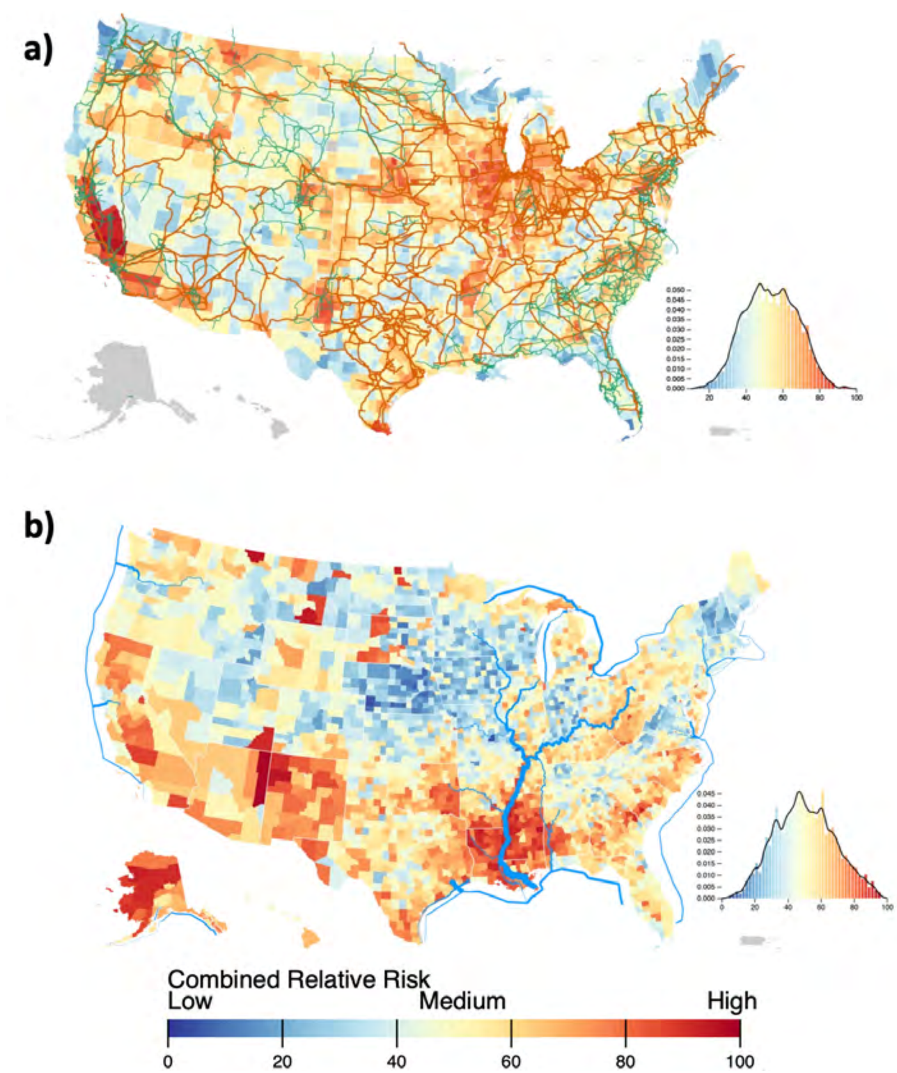

Figure 3. Maps produced from the SESRT platform illustrate the "hotspot" visualization and analysis capability of the user-defined, use-inspired interface. Panel a) shows the result of quantitatively combining the current level of risks in water availability and quality, land disturbance, and exposure to poor air quality. Orange and red shades indicate "hotspot" areas of these three risks co-existing to the highest degree relative to all U.S. counties. Also shown is the graphical overlay of high-voltage transmission lines (green ≥ 230kV and orange ≥ 345kV) across the nation's energy grid. Panel b) shows the result of combining risk metrics that convey the current levels of employment in fossil energy as well as demographic metrics of poverty, unemployment, and non-white population. Also shown as an overlay (blue lines) is the extent of major riverine and marine "highways" with the thickness of the lines depicting the relative total value of goods transported (coal, petro, food, chemical, manufacturing, and raw materials).

be visualized and explored with the triage platform that highlight other regions and multi-sector linkages, and these can guide model configurations, tested hypotheses, and experimental frameworks for a variety of detailed use case studies. Our ongoing efforts will continue to build upon our collection of historical and contemporary variables and expand upon our list of combinatory risk metrics in support of these screening-level multi-sector assessments.

3.2 Water Stress, Flood Risk, Poverty, and Race

As mentioned, many combinations of the risk metrics can be readily explored through the SESRT platform and provide more quantitative insights as to the areas of concern. For example, climate change, population growth, demographics, poverty, economic activity, and low-carbon energy transformation are but some of the major factors that can affect water demands. Looking at the current landscape of the combined risk of water stress and quality (Figure 4a), the risk is widespread and therefore it is difficult to distinguish exactly which areas of highest priority and/or concern would be. In considering only water stress and quality risks – most of the western U.S., the upper and mid-Mississippi regions, New England, the Mid Atlantic, and parts of the Southeast all convey a scattered map with locations of higher stress. The county-level results can be aggregated at the state level and ranked according to various factors in order to gain quantitative prioritization. For example, a "top 5 list" of the highest-at-risk states can be constructed by counting only the counties that are contained in the top 10% of the nationally pooled distributions (shown at the side of the maps in **Figure 4**) and summing those for every state according to either: total number of counties, percentage of counties in the state, or total population of those counties (**Table 2**). Based on any of these three categories, California stands out as the most salient state at risk with the highest or 2nd highest ranking. Other states that clearly stand out at higher risk are Illinois and Texas (with 2 top-five rankings). For the remainder of the results, the choice of the ranking criterion can have an important impact to a state's ranking. For example, over two-thirds of Delaware's counties experience combined water risk, placing it at the top of the percentage-of-counties ranking – but due to its lower total population as well as small total number of counties, it is at a distinct disadvantage to be top ranked in those ranking categories. Similarly, Nebraska having a high number of total counties gives the potential for a higher total number of counties under risk, and as such, it places 2nd in that category. However, its low total population and high total number of counties put it at a disadvantage to place in those ranking categories.

There are other important sensitivities to these highest-at-risk rankings. For example, the prioritization of a state to receive attention and assistance to mitigate water risks might also include a consideration of the extent of poverty. With this consideration in mind, we combine the water stress, water quality, and extent of poverty risk metrics, all with equal weighting. The results (Figure 4b) reveal important shifts in the overall landscape of risk as

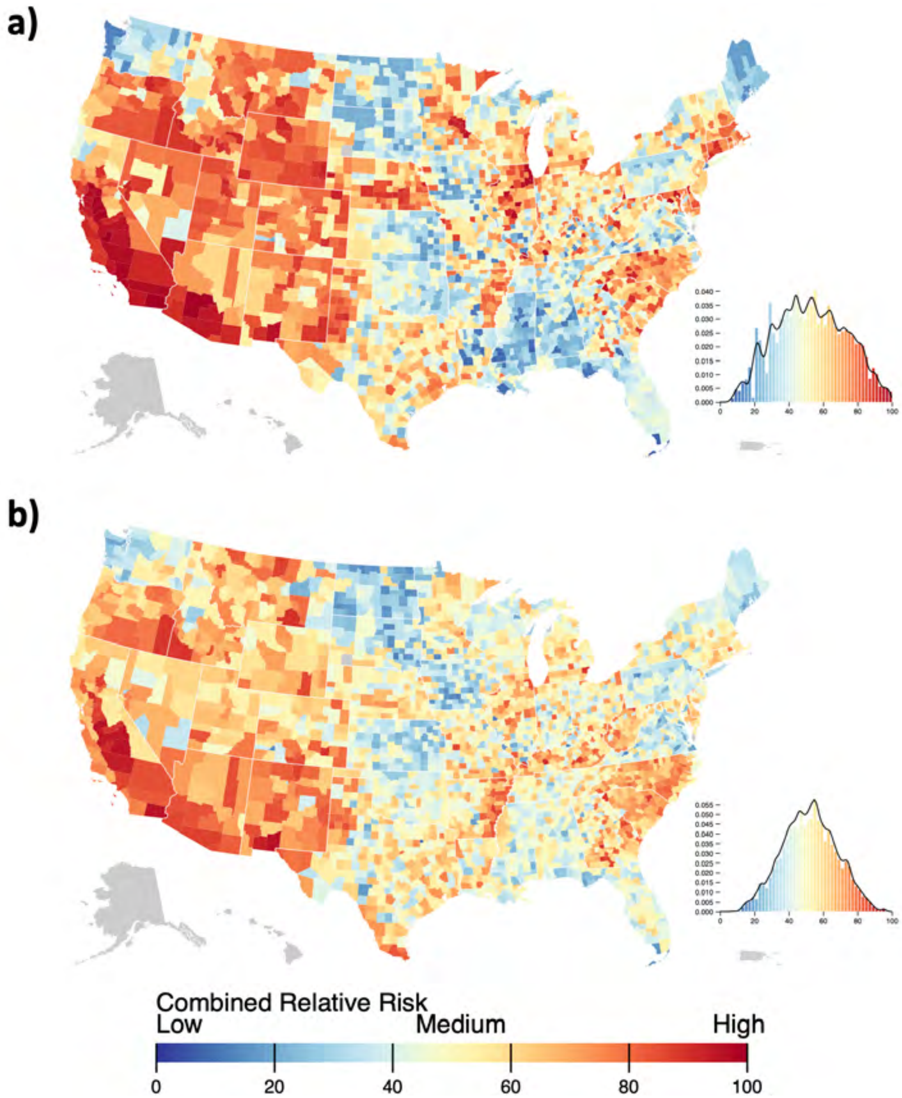

Figure 4. As in Figure 3, but highlighting the contrast between combinatory landscapes of: a) water stress and water quality risks; and b) water stress, water quality, and population below the poverty level.

Table 2. Summary of results from the combinatory risk metric combining water stress and water quality. The table presents the top-five ranked states (listed highest to lowest in the column) with the combined water stress and quality risk based on the following criterion: 1) total number of counties that are in the top 10% among the nationally-pooled county values; 2) percentage of counties of the state that are in the top 10% among the nationally-pooled county values; and 3) the totaled population of counties that are experiencing the highest 10% of stress.

Rank	Number of Counties Experiencing Stress		Percentage of Counties Experiencing Stress		Total Population of Counties Experiencing Stress	
1	California	35 (of 58)	Delaware	67%	California	38,219,489
2	Nebraska	21 (of 93)	California	60%	Illinois	8,911,663
3	Illinois	20 (of 102)	Wyoming	57%	Arizona	6,402,797
4	Texas	17 (of 254)	Connecticut	50%	North Carolina	4,120,372
5	Montana and Colorado	16 (of 56 & 64, respectively)	Utah	48%	Texas	3,383,288

Table 3. As in Table 2 – but for the combinatory risk metric of water stress, water quality, and population below the poverty level.

Rank	Number of Counties Experiencing Stress		Percentage of Counties Experiencing Stress		Total Population of Counties Experiencing Stress	
1	North Carolina	35 (of 100)	New Mexico	61%	California	16,393,766
2	Texas	34 (of 254)	Arizona	53%	New Mexico	6,295,727
3	Kentucky	28 (of 120)	California	41%	Texas	5,065,099
4	California	24 (of 58)	North Carolina	35%	Colorado	4,937,036
5	New Mexico and Georgia	20 (of 33 & 159, respectively)	Oregon	33%	West Virginia	3,927,185

Table 4. Summary of results from the combinatory risk metrics considering: 1) flood and water quality; 2) flooding, water quality, and poverty; and 3) flooding, water quality, poverty, and nonwhite population. The table presents the top-five ranked states (listed highest to lowest in the column) with the combined risk based on the percentage of counties of the state that are in the top 10% among the nationally-pooled county values.

Rank	Flood and Water Quality		Flood Risk, Water Quality and Poverty		Food Risk, Water Quality, Poverty, and Non-white Population	
1	West Virginia	67%	West Virginia	60%	North Carolina	62%
2	Vermont	50%	Kentucky	54%	South Carolina	51%
3	New Hampshire	50%	North Carolina	48%	Arizona	40%
4	North Carolina	45%	Arkansas	35%	West Virginia	31%
5	Kentucky	40%	Arizona	33%	Kentucky and Georgia	30%

well as to the highest-at-risk state rankings (**Table 3**) discussed above. Many of the regions across the northern U.S. at higher risk from only water stress and quality are buffered, and most of the highest at-risk counties are in states across the southern half of the United States. This impact is also clearly seen in the top-five ranked state results. With the addition of poverty into the risk assessment, Illinois drops out of all the top rankings considered, in addition to Connecticut, Delaware, and Montana. The most notable addition to the highest rankings is New Mexico, making into all three of the highest-ranking lists. Other additions contributing to this southern shift of states within the top rankings include Georgia, Kentucky, and West Virginia. One exception to this overall shift is Oregon, in which one-third of its counties at water stress and poverty risk place it just within the top ranking of that category (but absent in the water-only risk results). Nevertheless, there are two states that stand out as the highest ranked across both the combined risk metrics: California and Texas.

Like water stress, resiliency to flooding is not simply a case of the risk of flooding itself and its consequences which damages property and contaminates water supplies, but also the ability of communities to rebuild and repair damage, which can be hindered by poverty (e.g. McDermott, 2022; Hallegatte *et al.*, 2020) and may also carry important equity dimensions. We can examine all these facets through a successive combinatory analysis provided by the SESRT framework. To first order, we find that as the risk metric incorporates poverty and equity (i.e., nonwhite population) successively, the hotspots (**Figure 5**) as well as the top-ranked states (**Table 4**) move predominantly toward the southern half of the United States. Most notably, the highest ranked states in the Northeast, in terms of the physical risk of flooding, are diminished when poverty and nonwhite population factors are incorporated. Conversely, there is a prominent clustering and high ranking from all the risk factors combined (i.e., flood, water quality, poverty, and nonwhite population) in the Carolinas and surrounding states (West Virginia and Georgia). Irrespective of these notable shifts in the landscapes of risk – West Virginia, North Carolina, and Kentucky consistently rank high and experience all these combinations of risk across the largest portion of their counties.

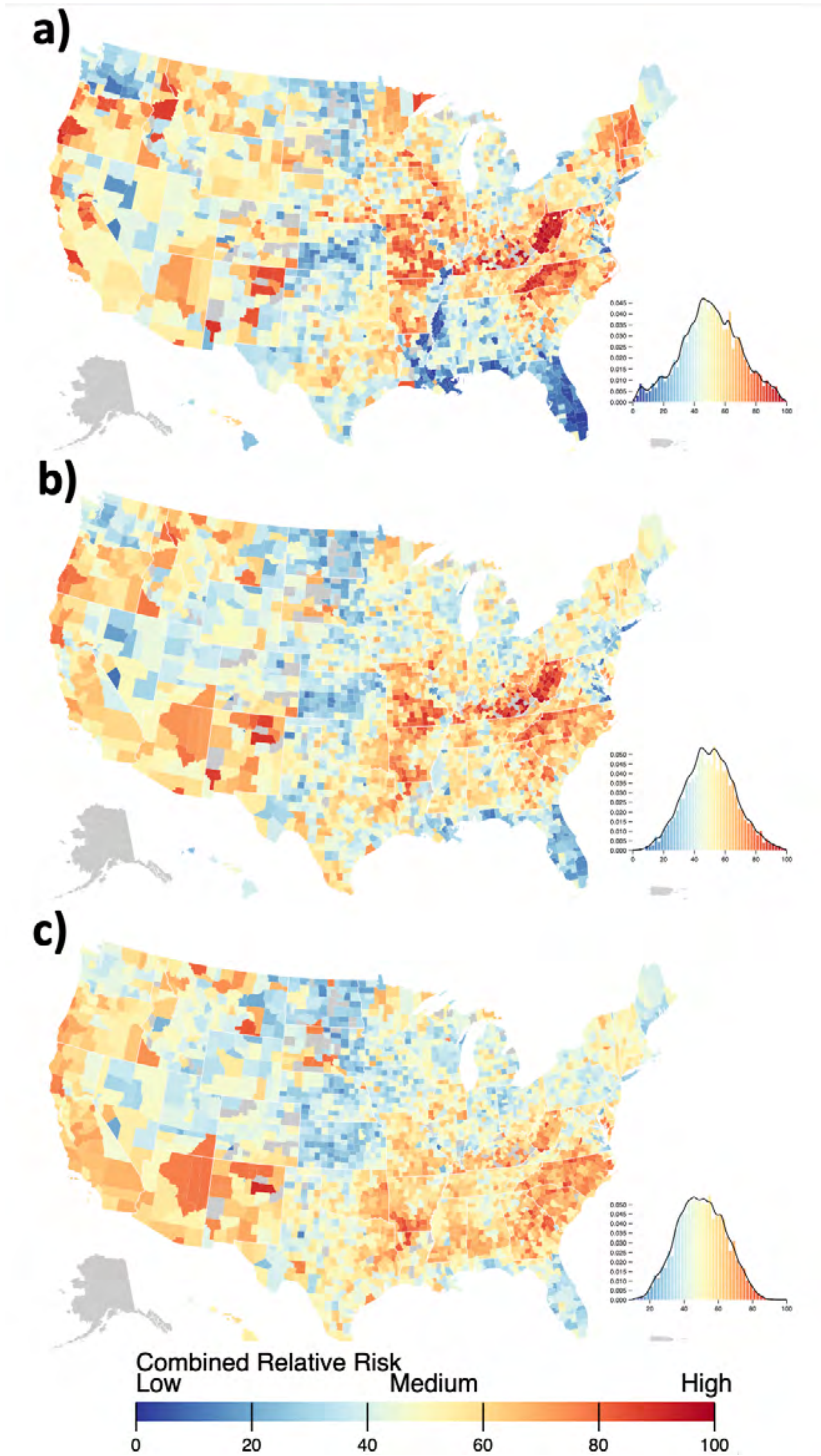

Figure 5. As in Figure 3, but highlighting the contrast between combinatory landscapes of: a) aggregate flood risk and water quality risk; b) aggregate flood risk, water quality risk, and population below the poverty level; and c) aggregate flood risk, water quality risk, population below the poverty level, and non-white population.

3.3 Cropland under risk of erosion and water stress

The U.S. is a major producer and exporter of food and agricultural products (e.g. FAO, 2022; USDA, 2021). Cropland in the U.S. is exposed to several risks, among which is water stress, but can vary considerably by region. An initial visualization (**Figures 6 and 7**) and tabulation of the cropland area data (**Table 5**), which is readily downloadable from the SESRT platform, indicates that among the top-10 states that contain the highest amount of cropland area – all but one (Montana) contain or flank the sharp east-west gradient of Climate Moisture Index (CMI, see

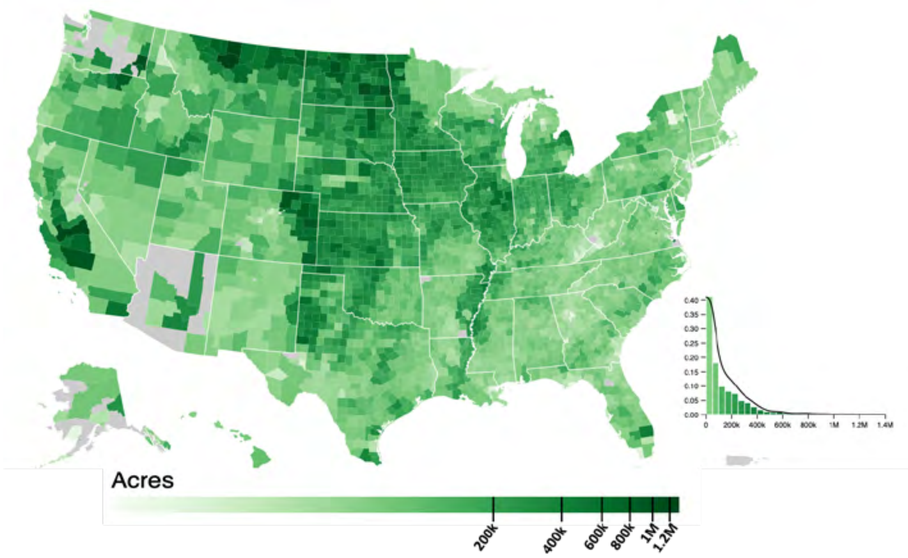

Figure 6. Map displays cropland area (acres) across U.S. counties. Gray shaded areas denote missing data and/or no cropland recorded for county. Map results based on data retrieved from the USDA National Agricultural Statistics Service (NASS). See text for further information.

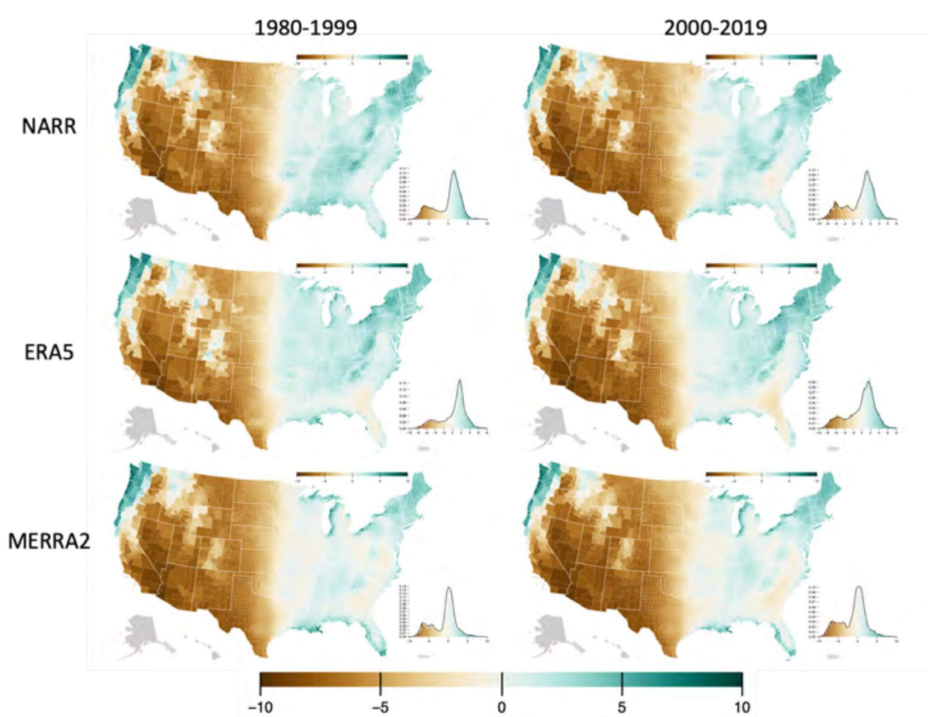

Figure 7. Maps display Climate Moisture Index (CMI- unitless) multiplied by a factor of 10 across U.S. counties averaged for two 20-year time periods (left panels 1980-1999 and right panels 2000-2019) based on the meteorological driver data from the three reanalyses data sets compiled for the platform (top panels NARR, middle panels ERA5, and bottom panels MERRA2). See text for further information regarding the calculation of CMI as well as the reanalyses data.

Table 5. Summary of results from combinatory metrics considering: 1) cropland area (acres); 2) area of cropland experiencing "water stress" (acres) for the 1980-1999 period (i.e., left panels in Figure 7); and 3) area of cropland under water stress (acres) for the 2000-2019 period (i.e., right panels in Figure 7). The table presents results for the top-ten ranked states in terms of total cropland area (listed highest to lowest). Table values in parentheses indicate percentage of total cropland area. A county is considered to experience "water stress" (and thus its cropland area) if its climate moisture index (CMI) is below −0.1 (or a value of −1 in the panels shown in Figure 7). In terms of total cropland across the U.S., these top-10 states comprise nearly 60% of the total national cropland area (396,372,177 acres). The rightmost column presents the change in cropland area (acres) under water stress from the 1980-1999 to the 2000-2019 periods. The results for cropland area under water stress are the mean result from the three reanalyses' CMI estimates.

State	Cropland area (acres)	Cropland experiencing "water stress" 1980-1999 (acres)	Cropland experiencing "water stress" 2000-2019 (acres)	Change in cropland experiencing "water stress" (acres)
Texas	29,359,599	25,925,706 **(88%)**	26,700,990 **(91%)**	775,284
Kansas	29,125,505	23,999,420 **(82%)**	25,508,792 **(88%)**	1,509,372
North Dakota	27,951,676	27,652,883 **(99%)**	27,303,470 **(98%)**	-349,413
Iowa	26,545,960	5,593,063 **(21%)**	7,744,015 **(29%)**	2,150,952
Illinois	24,003,086	-	293,863 **(1%)**	293,863
Nebraska	22,242,599	20,633,967 **(93%)**	21,767,371 **(98%)**	1,133,404
Minnesota	21,786,756	10,208,863 **(47%)**	10,250,377 **(47%)**	41,514
South Dakota	19,813,517	18,893,072 **(95%)**	18,917,555 **(95%)**	24,483
Montana	16,406,300	13,694,876 **(83%)**	13,769,486 **(84%)**	74,611
Missouri	15,599,446	758,126 **(5%)**	988,470 **(6%)**	230,343
Total	232,834,444	146,601,850 **(63%)**	152,255,920 **(65%)**	5,654,070

Appendix A.3 for further details) that delineates regions of precipitation excess (CMI>0) or deficit (CMI<0). For the case of when a county achieves a negative CMI value, this would be indicative of a salient transition into a "water stress" situation, in that irrigation will likely be required to sustain water demand for rainfed crops. We tighten this convention by assigning a threshold for a county under "water stress" when its CMI drops below -0.1 (and therefore so is the cropland within it). From this criterion, the decadal-scale shifts in CMI across the timespan of the data (between the 1980-1999 and 2000-2019 averaging periods) reveal that in all but one state (North Dakota), the total area of cropland within the top-10 cropland area states experiencing water stress increases (Table 5). The largest changes, in terms of absolute and relative change, occur in Kansas (over 1.5M additional acres, a 6% increase), Iowa (over 2.1M additional acres, an 8% increase), and Nebraska (over 1.1M additional acres, a 6% increase). Another notable change is the emergence of Illinois from initially none to over 293,000 acres of farmland located in counties experiencing water stress (by our definition). Overall, over the past four decades (1980-2019) 5.5 million acres of additional farmland across the top-10 cropland-area states are being exposed to water stress.

While these recent trends in water stress locate formidable risks across the country's largest cropland areas, in other areas, several risks may co-exist and reinforce each other (such as land conditions and water stress), threatening yields and increasing the chances of potential negative impacts in agricultural income and local livelihoods – especially in areas of poverty. The triage platform allows an efficient assessment of major cropland areas subject to multiple risks at the National and State levels, as also as identifying if these places are already subject to social challenges, high poverty levels or unemployment rates. **Figure 8** highlights these combinations. While panels a, b and c show the distribution of water stress, populations below poverty level and highly erodible land taken individually, panels d, e and f combine each two of these variables. These combinations reduce the frequency of higher risk areas, mainly in the Eastern side of the country, although several "hot spots" arise. As example, water stress and highly erodible land (panel e) reinforce each other at central areas along the borders of New Mexico with Texas and Colorado as well as between Kansas and Nebraska. Combining population below poverty level to these (panel g), and comparing it with cropland area (panel h), allows to identify the highest risk areas for cropland production due to water stress and erosion and how they overlap with higher poverty levels, highlighted in panels g and h. Among the most salient areas with these multi-dimension risks include counties within California, Texas, New Mexico, Montana, and Washington.

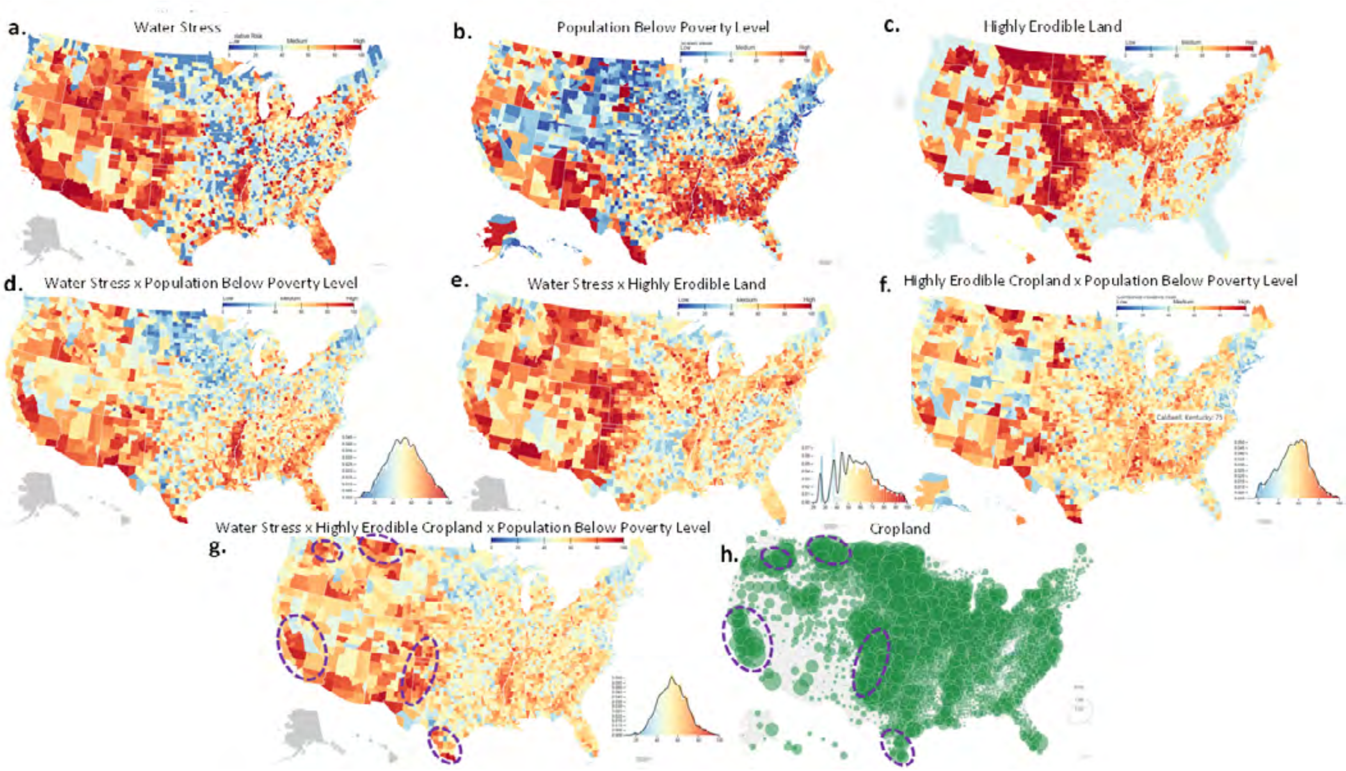

Figure 8. Maps indicating U.S. conditions of: a) water stress a), b) population below poverty line, c) highly erodible land, as well as combinations of those in panels d) – g); and h) cropland areas.

3.4 Exploring the intersection of physical and transition risks

We can use the triage platform to provide insights about both transition and physical risks. In terms of transition risk, we can look at employment in fossil fuels (**Figure 9a**), which suggests potential risk of economic hardship if the country moves away from fossil fuels and toward low-carbon alternatives. We see that Texas, Louisiana, Oklahoma, Kansas, Wyoming, North Dakota and West Virginia stand out as having high shares of people employed in jobs related to fossil fuels. We can then combine this metric with data on the population below the poverty level (shown in **Figure 9b**). Areas that already have a high poverty rate and have the potential for significant job loss with a transition away from fossil fuel use are particularly vulnerable to economic distress (**Figure 9c**). The triage platforms can identify individual counties where this combined risk is particularly high. These areas would be good candidates for targeted job retraining programs or green jobs development to help ameliorate the transition risks.

Looking at employment in fossil fuels also tells us where the most fossil assets are located. Combining that information with flood risk (shown in **Figure 9d**), we can identify fossil assets at risk of flooding. The resulting combined map (**Figure 9e**) indicates that areas of West Virginia and western Pennsylvania have high risks of physical damage to fossil assets due to flooding. Areas to the east and west of the lower Mississippi River, as well as pockets along the Gulf Coast, also have high physical risks. Fossil assets along the Gulf Coast face additional physical risks due to sea level rise, hurricanes and storm surge. Areas identified as facing high physical risks should be further investigated to consider investments in protective measures and/or relocation. Combining these aspects of transition and physical risk related to fossil fuels highlights areas particularly vulnerable to these combined risks.

3.5 Local Impact Assessment – A Case Study

The following case study applies the risk-triage approach from a local (town/county) perspective. Background: The owner of a company is being offered incentives to move their food processing business to a town in Vandalia, IL which is in Fayette County, IL. They are looking to locate in an area with access to reliable infrastructure (including energy and transportation), minimal flood/drought risk, and a decent economy to maintain and support their employees. They may also be interested in expanding into growing some of their own produce and would like to know if the area is conducive to that activity. The SESRT platform can help evaluate these concerns by reviewing different landscapes of socio-economic, health, and environmental risk.

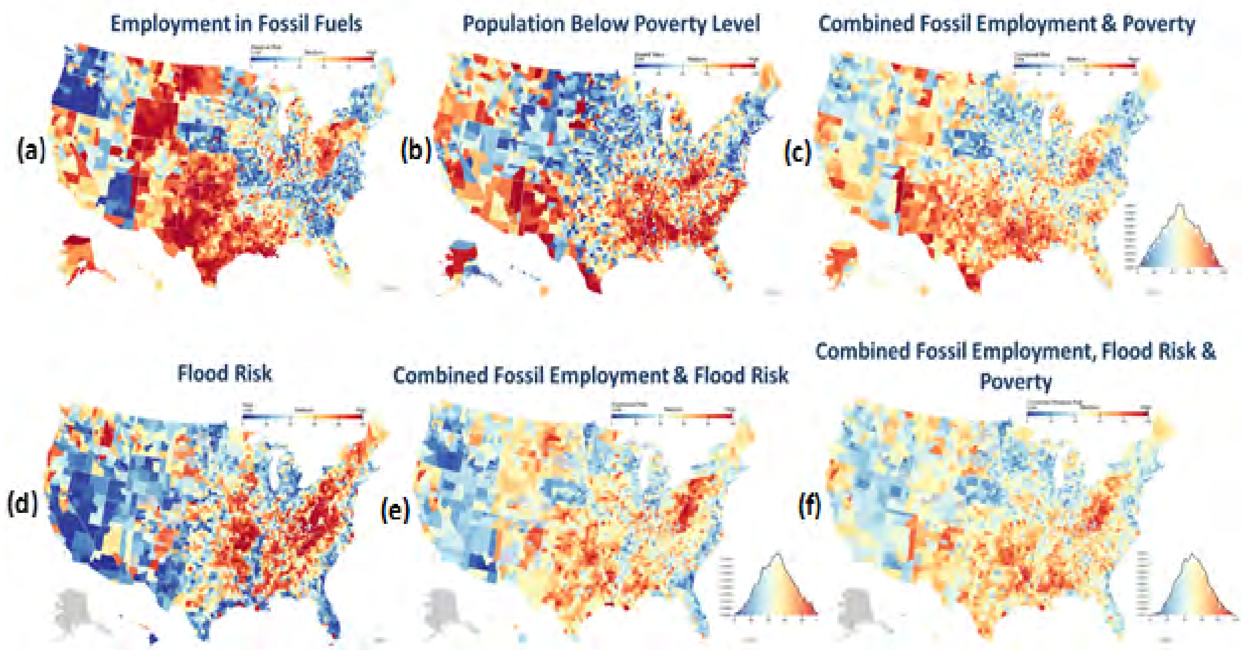

Figure 9. Maps indicating transition and physical risks related to fossil fuels: (a) employment in fossil fuels (transition risk); (b) population below poverty level; (c) combined fossil employment and poverty (transition risk); (d) flood risk; (e) combined fossil employment and flood risk (physical risk); and (f) combined fossil employment, flood risk and poverty (both transition and physical risk).

Concern #1: Flood/Drought Risk

Looking at Fayette, IL over the water stress dataset from 2010 to 2015, there doesn't appear to be any years of significant water stress (**Figure 10**). Some of the surrounding counties may experience significant water stress during some years. There is light to moderate risk of drought when looking through the various years and models of the hydrologic drought index. The climate moisture index is around 0 for this area which means it is not an area of extreme heat or cold on average. There is a concern when looking at the 100-year flood as the results show that this area is under high risk (**Figure 11a**).

Concern #2: Reliable Infrastructure

We can define reliable transportation infrastructure as access to major highways and waterways that are in proximity and not located in areas prone to extreme events that would degrade the quality and reliability of the infrastructure. We can also look at the surrounding areas to evaluate if there is redundancy in the infrastructure. The location of Fayette, IL has prime access to major transportation infrastructure including road, rail, and nearby major waterway. There are some redundancies in the highways as it appears to have access from north to south and east to west. Both highways and rail run through the county (**Figure 11b**). The Mississippi River is near allowing freight transport of food. While there is low concern regarding droughts in this area, there is a significant flood risk which could impact the transportation infrastructure. In addition to transportation infrastructure, the SESRT provides information on the energy infrastructure. Figure 9c shows major electrical transmission lines run through Fayette, IL (> 345kV).

Concern #3: Local Economy

The per capita personal income from 2018 was ~$30k/person (**Figure 12a**). This is on the lower end of personal income. When looking at the different areas of employment, it appears that approximately 6% of employed people are in the category of agriculture, forestry, fishing and hunting while 18% are employed by healthcare and social assistance. The SESRT also provides information on population and unemployment. Fayette, IL has ~4% unemployment rate which is lower than the national average (not shown). Unfortunately, 16% of the population in this county is below the poverty level which is higher than the national average (**Figure 12b**). The population under 18 is 21% and over 65 is 18%, which places it within an average population age distribution relative to the national values.

Concern #4: Ability to successfully grow crops

Figure 10c shows Fayette, IL with poor water quality (0.8) but low to negative irrigation deficit which shows that water availability shouldn't be a concern. Although, as mentioned previously, there is significant concern of flooding. It is noted that there is no critical habitat of concern in Fayette, IL.

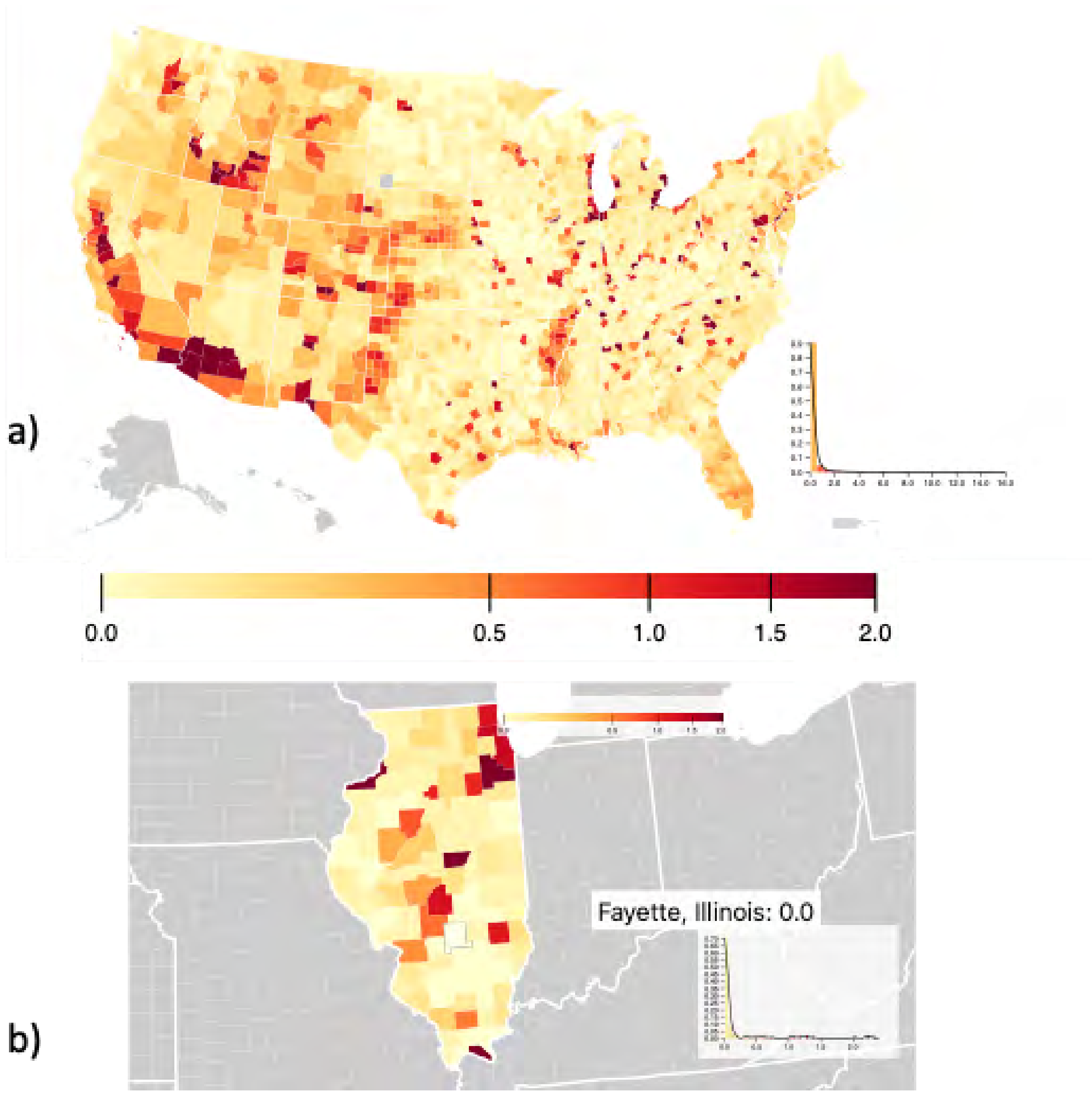

Figure 10. Maps display the average water stress (unitless) from 2010-2015 for: a) the U.S. (top panel) as well as; b) for the state of Illinois (bottom panel). In the bottom panel, the result for the county of Fayette, IL is highlighted to note that it has an average water stress of 0 over this period.

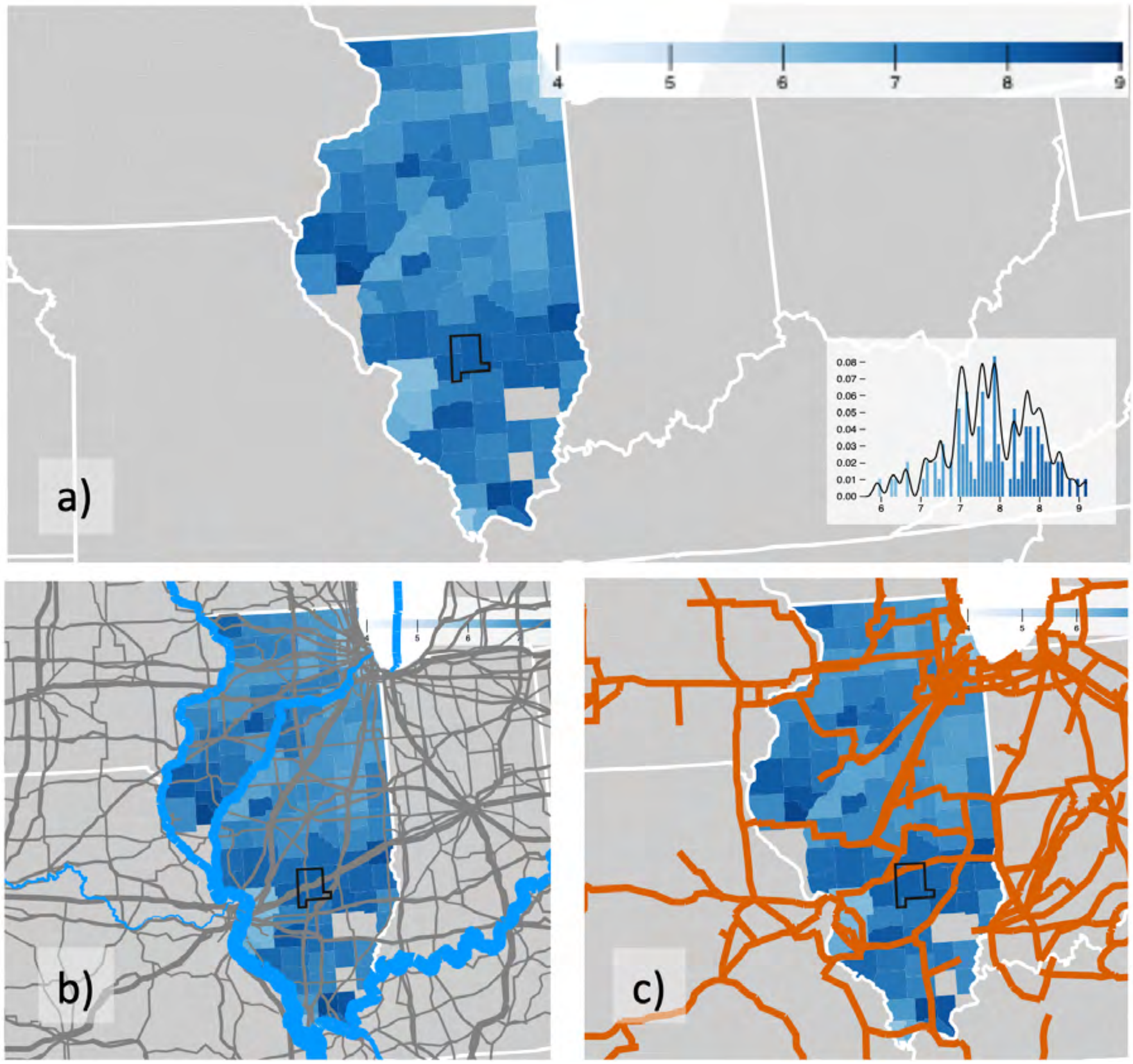

Figure 11. Maps depicting: a) the 100-year flood risk for Illinois, and depicting the high flood risk value of 8 out of 9 for Fayette, IL, and b); flood map that includes overlays of major highway (thin gray lines), railways (thick gray line); as well as waterways (blue lines); and c) flood map that includes overlay of electrical transmission lines at 345 kV, and indicating that these transmission lines run through Fayette, IL.

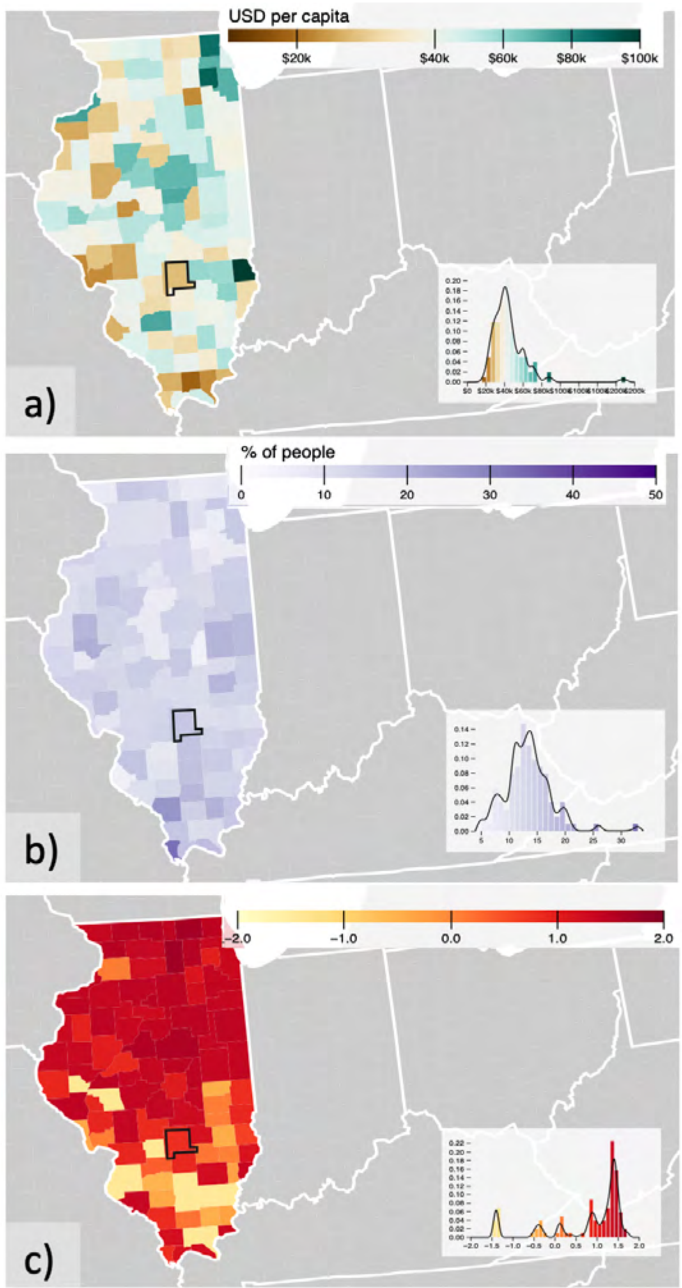

Figure 12. Maps indicate: a) the per capita personal income across Illinois (based on the 2019 Census data collected). Fayette, IL is on the lower end of personal income with a value of $40k/person; b) the percentage of population below the poverty level across Illinois. Fayette, IL has a moderately high percentage (16%) of people below poverty level relative to other counties; and c) the level of water quality across Illinois. Fayette, IL has some concerns regarding water quality with a ranking of 0.8 out of 2 where 2 is the worst ranking.

Combined overall risk evaluated on the SESRT

If we ranked all the metrics as listed below, we find that the overall risk given our prioritized concerns is about at 57/100, which we would consider a moderate risk. In comparison with the state of IL, this is about average or a bit lower than average risk (**Figure 13**). The resultant aggregate metric was obtained through the following combinatory weights:

- Maximum: Water Stress, Water Quality, Flood Risk, Temperature Stress, Poverty Level, and Unemployment
- Medium: Highly Erodible Cropland, Land Disturbance
- Minimum: Employment in Fossil Fuels, Population under 18, Population over 65, and Nonwhite Population

In conclusion, after evaluating Fayette, Il with the SESRT, the company determined that while there is significant risk of flooding and a poor economy, the overall risk given the

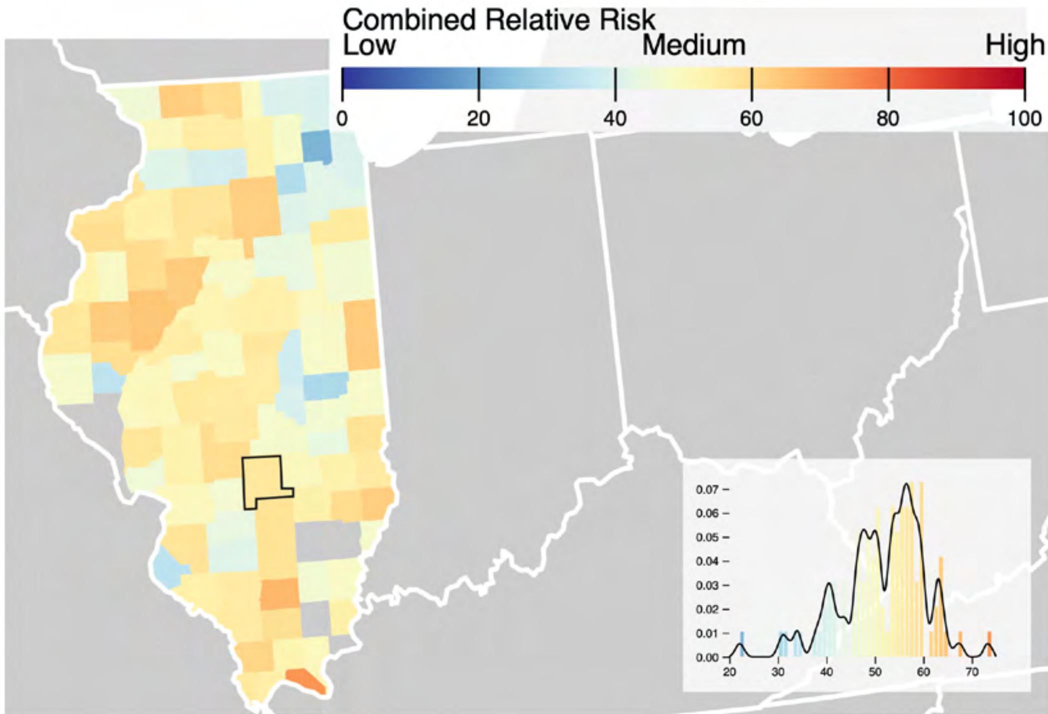

Figure 13. Map depicting the overall risk that results from combining all factors from Figs. and weighing them according to the business owner's main concerns. Fayette, IL has a moderate overall risk.

company's prioritized concerns is average. It should also be noted that the overall combined metrics did not include the enormous benefit of access to reliable transportation infrastructure (road, rail and waterways). The risk of flooding in terms of the manufacturing plant can be minimized by locating the building outside the immediate flood zones. While poor economy was listed as a risk, the company likes to view it as an opportunity to help contribute to improving the situation by adding to employment and stimulating the local economy. The opportunity to look at growing crops appears to have some potential given the high level of agriculture already in the area, but also some concerns with water quality, land disturbance and flood potential. Investment into growing their own crops would need to be investigated further.

4. Summary and Closing Remarks

We have described a Socio-Environmental Systems Risk Triage (SESRT) platform that is designed to serve as visualization tool for multi-sector, combinatory risk analysis and data download. The risk-triage platform is intended to be a tool in and of itself and is publicly available. As we continue to develop our platform across more of these landscapes, it can be used to motivate and guide additional analysis and deeper dives by the MSD research community. The platform has also generated broader interest and support from various stakeholders to incorporate and integrate other landscapes of hazards and risks such as: biodiversity, health, and systemic racism. The platform has been designed to readily incorporate additional data and model results as well as support an open-science research community. Our source code is on GitHub (github.com/cypressf/climate-risk-map). You can view discussion of technical planning and discussion on our GitHub issues link (github.com/cypressf/mit-climate-data-viz/issues).

We present several illustrative examples that highlight features and capabilities of the SESRT platform. We show that in terms of the combined air-energy-land-water risks, the most prominent "hotspots" are located across California, the upper and lower Mississippi basin, the Ohio River basin, Texas, the Southeast as well as Mid-Atlantic states. Concurrently, we find regions of the nation with the largest portion of employment in the fossil fuel industry, along with high levels of poverty and unemployment flank the lower portions of the Mississippi River. National and global actions to reduce greenhouse emissions could limit risks to land, water, and air quality in the upper basin, but at the same time impacts on the fossil fuel industry could have significant employment impacts in the lower Basin where poverty and unemployment are already disproportionate. Overall, these highlight the potential locations of and connections between contrasting regional effects of any low-carbon energy transition strategy.

Another inspection with the SESRT platform that considers state-to-state rankings of severe water stress shows regions that are robust (i.e., California, Illinois and Texas) but also sensitive to the choice of criterion upon which to base a ranking of water risk (Delaware and Nebraska). Further considerations that include socio-demographic conditions, such as poverty, can have a substantial impact on these rankings. The combination of poverty and water-stress into the risk ranking results in a notable shift to southern states that rank among the highest (New Mexico, Georgia, Kentucky, and West Virgina). A similar impact is seen when combining flood risk with poverty and ethnicity (i.e., non-white population), with a southerly shift to "hotspots" of combined risk that incorporate the socio-demographic dimensions. Further echoing these water issues, when we alternatively combine these metrics with the extent of cultivated lands, we find that over the past few decades, at least an additional 5.5 million acres of farmland are in counties exposed to increased water stress, with Iowa, Kansas, and Nebraska the top three states. However, this landscape changes considerably when combined with risks in land erosion and poverty, and the "hotspots" move to counties within California, Texas, New Mexico, Montana, and Washington. We further illustrate the platform's ability to explore multiple facets of risk through a focus on transition risks. We show that there is a large region across the south-central U.S. and Appalachia that experiences relatively high levels of fossil fuel employment and poverty – and underscores a transition risk to low-carbon energy proliferation.

These examples of co-existence of interconnected risks provide guidance and motivation for deeper-dive use case studies on human-natural system interactions; grid resiliency; and transportation infrastructure (Section 3). There are, of course, many other overlays and different compounding risks that can be explored with the triage platform that highlights other regions or different use cases. In another demonstration, we also highlight the ability of the platform to scan multiple sectors and overlays and provide a combinatory risk inspection at a county level. The result provided a multi-dimension assessment of risk for a (hypothetical) company who had interest in expanding their business within a particular county (Fayette, IL).

In view of these aspects to our SESRT platform, as part of our ongoing efforts we will continue to build upon our collection of historical and contemporary variables and expand upon our list of combinatory risk metrics. We will seek opportunities to partner and complement these efforts to create a comprehensive and inclusive repository for data-driven science in multisector dynamics. Thus far, our SESRT platform has been focused on historical and contemporary landscapes of data and combinatory metrics. Another key development task under this effort will be to expand the triage platform to provide a comprehensive assessment of future projections that incorporates uncertainty. In doing so, we expect these advances to provide insights that identify: the extent that trajectories from current, co-existing risks can compound and intensify; and the extent to which new and unprecedented risks can emerge as "hotspots" for potential tipping points. Given the ability of the SESRT platform to explore many different combinations of these emerging risks, we also expect the insights that we obtain can help prioritize and identify locations for deeper-dive studies that can assess specific actions and adaptations that are needed to reduce, remove, or reverse risks; as well as the extent to which insights gained from one region/location could be applicable to other locations facing similar risks.

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Appendix A. Data Sources

There are a number of on-line tools that exist and many of them provide capabilities that have been discussed herein. Such platforms include (but are not limited to):

- Data.gov: U.S. Government's open data portal
- EPA: EnviroAtlas Interactive Map: https://www.epa.gov/enviroatlas/enviroatlas-interactive-map
- Environmental Dataset Gateway (edg.epa.gov)
- EJScreen (ejscreen.epa.gov)
- EJAtlas: Global Atlas of Environmental Justice (ejatlas.org)
- EIA: U.S. Energy Atlas (https://atlas.eia.gov/pages/maps) – mapping and data for energy infrastructure, resources, and disruptions.
- ESGF: Earth-System Grid Federation – the one-stop site for CMIP, CORDEX, and a variety of Earth-System Model data across major international research institutes.
- DOE: "Open Energy Data" (https://www.energy.gov/data/open-energy-data)
- Environmental Quality Index (EQI - www.epa.gov/healthresearch/environmental-quality-index-eqi)
- FEW-ViewTM: Food, Energy, and Water Data Science for Supply Chains (fewsion.dtn.asu.edu)
- NASA: Worldview (https://worldview.earthdata.nasa.gov)
- NSF: NCSES (National Center for Science and Engineering Statistics) Survey Data (https://ncsesdata.nsf.gov/home)
- USGS National Map Viewer (https://noaa.maps.arcgis.com/home/index.html)
- NOAA: GeoPlatform (https://noaa.maps.arcgis.com/home/index.html)

Each of these platforms carry with them a unique strength and feature, yet in none of these does it provide the ability to selectively combine (and weight) metrics to assess co-occurring, compounding, and co-evolving threats. As mentioned, our platform has been developed in order for the user to efficiently explore and assess these amalgamate effects. We have drawn data from a number of these data and visualization platforms. In Section 2, we described variables that have been used as the basis for our combinatory risk metric visualization and analyses. Below we provide a description of variables not included in the combinatory metrics webpage, yet we have incorporated into the platform as supplementary data for visualization and download. Our data collection is ongoing, and so the summary presented here is likely not commensurate to the data collection currently on the platform. Further documentation will be provided when salient augments to the data collection have been compiled.

A.1 Energy and Economy

As the global energy and economy systems are closely linked, data under these categories have been initially collected under two main considerations: employment across selected energy sectors; and the associated costs of energy across various sectors. We gathered data from the 2017 U.S. Energy and Employment Report (https://www.usenergyjobs.org/) and our platform provides the county-level statistics on total number of people employed in: 1) fossil fuels, 2) renewable energy, 3) energy efficiency, 4) transmission/distribution/storage, and 5) motor vehicles. For energy expenditures, we have gathered data available from the State Energy Data System (SEDS) provided by the U.S. Energy Information Administration (EIA). The data is directly available via download at www.eia.gov/state/seds/. Our current collection of data provided on the platform includes 2018 statistics on: 1) annual energy expenditure per capita (USD per person); 2) annual residential energy expenditure per capita (USD per person); 3) annual transportation energy expenditure per capita (USD per person); 4) energy expenditure as share of GDP (%); 5) residential energy expenditure as share of GDP (%); and 6) transportation energy expenditure as share of GDP (%).

A.2 Land

The current collection of variables provides information on land use, the quality of the land, wildfire risk, endangered species, as well as information on the market value and the extent of insured cultivated lands. In terms of land use, value, and insurance, we have extracted data from the National Agricultural Statistics Service (NASS, data is available at https://quickstats.nass.usda.gov/), and the current collection provided on the SESRT platform includes: 1) area (acres) of agricultural land; 2) area (acres) of land for forestry; 3) area coverage (acres) of pastureland; 4) area (acres) of insured farmland; and 5) the estimated market value of the land and buildings (in USD) in farms.

In terms of the quality of land, we have extracted data from the U.S. Department of Agriculture's (USDA) National Resources Conservation Services (NRCS) portal that indicate: 1) acres of highly erodible cropland (HEL), which is land that has an erodibility index of eight or more as defined from the National Food Security Act Manual (NFSAM). The erodibility index (EI – technical description provided at https://directives.sc.egov.usda.gov/rollupviewer.aspx?hid=29340) provides a numerical expression of the potential for a soil to erode considering the physical and chemical properties of the soil and the climatic conditions where it is located. The higher the index, the greater the investment needed to maintain the sustainability of the soil resource base if intensively cropped. The HEL procedure results in pointwise "pindrops" on maps to indicate locations where there are 10,000 acres of HEL land. For our county-level presentation of the data on the SESRT platform, we summed the total number of these HEL pindrops within each county – and summed the total subsequent area coverage. These pindrop maps for 1982 and 2017 are available (respectively) at: https://www.nrcs.usda.gov/Internet/NRCS_RCA/maps/m14601hel82.png and https://www.nrcs.usda.gov/Internet/NRCS_RCA/maps/m14598hel17.png. For our analyses, we obtained the original shapefiles of the point data (Tcheuko, Lucas, personal communication, FPAC-NRCS, Beltsville, MD <Lucas.Tcheuko@usda.gov, March 30, 2021).

The SESRT data collection also includes a land disturbance index obtained from the Environmental Protection Agency's (EPA) Environmental Quality Index (EQ Index) collection (U.S. EPA, 2020). Low index scores indicate higher environmental quality, and higher index scores mean lower environmental quality. The land disturbance index included five data sources representing five constructs: (1) Agriculture, (2) Pesticides, (3) Facilities, (4) Radon, and (5) Mining Activity. The data sources identified for this domain include: 2007 Census of Agriculture [19], 2009 National Pesticide Use Database [18], EPA Geospatial Data 12 Download Service [20], Map of Radon Zones [21], and Mine Safety and Health Administration (MSHA) mines data [22]. The MSHA mines database is a data source new to EQI 2006-2010. Also, the National Geochemical Survey database used in EQI 2000-2005 was not used in EQI 2006-2010. The data can be downloaded from https://edg.epa.gov/EPADataCommons/public/ORD/CPHEA/EQI_2006_2010/, and a report and overview of the Environmental Quality Index can be downloaded at: https://www.epa.gov/healthresearch/environmental-quality-index-eqi#overview.

A.3 Climate and Water

We have compiled three widely used reanalysis datasets: 1) MERRA-2; 2) ERA5; and 3) NARR (**Table A1**) on a monthly timescale to derive various climate-related risk metrics over the United States under contemporary conditions. We examine these risk metrics during three time periods: 1980-1999, 2000-2019, and 1980-2019. The use of multiple reanalysis data allows us to account for several sources of uncertainties in risk assessment attributed to the choice of reanalysis products, temporal period and spatial resolution. This historical climate risk assessment could serve as the baseline against foresights into potential tipping points and instabilities in the future climate change environment.

The climate-related risk metrics examined in our triage prototype focus on different hydrological and temperature extreme conditions (**Table A2**). Metrics are derived at the native spatial resolution of each reanalysis data for all

Table A1. Characteristics of various reanalysis products used to derive climate risk metrics. MERRA-2, ERA5, and NARR represent the Modern-Era Retrospective analysis for Research and Applications, Version 2 (Bosilovich *et al.* 2016), the fifth generation of ECMWF atmospheric reanalyses (Malardel *et al.* 2015), and the NCEP North American Regional Reanalysis (NARR, Mesinger *et al.* 2006), respectively.

Reanalysis Product	Domain	Period of Record	Timestep	Spatial Resolution	Assimilation Method
MERRA2	Global	1980-present	Sub-daily	0.625˚x0.5	3D-VAR
ERA5	Global	1979-present	Sub-daily	0.25˚x0.25	4D-VAR
NARR	North American	1979-present	Sub-daily	32km	3D-VAR

Table A2. Various derived climate-related risk metrics. All the metrics are derived for three periods, including 1980-1999, 2000-2019, and 1980-2019.

Name	Unit	Description
PRC	mm/year	mean annual precipitation
PET	mm/year	mean annual evapotranspiration calculated using modified Hargreaves method (Droogers & Allen, 2002)
CMI	-	climate moisture index based on prc and pet
RO	mm/year	mean annual runoff calculated using Turc-Pike model (Yates, 1997)
DEF	mm/year	irrigation deficit (pet – prc)
GW	mm/month	minimum of the monthly runoff climatology
WET	mm/month	98th percentile of monthly runoff time series
DRY	mm/year	5th percentile of annual runoff time series
HT	°C	Maximum monthly temperature

three time periods. Monthly potential evapotranspiration (PET) is calculated based on monthly mean surface air temperature, monthly mean temperature diurnal range, and monthly mean precipitation using modified Hargreaves method (Droogers and Allen, 2002). The Climate Moisture Index (CMI) is one type of drought indicator and calculated as the difference between annual precipitation (PRC) and potential evapotranspiration (PET) as shown in the equation (1). Positive CMI values indicate wet or moist conditions, while negative CMI values indicate dry conditions. The closer to 1.0 (-1.0) CMI value is, the stronger the wet (dry) condition represents. Driven by each of the abovementioned reanalyses data sets, monthly runoff (RO) is calculated based on the monthly precipitation and potential evapotranspiration using the Turc-Pike model (Yates, 1997). Irrigation deficit (DEF) is calculated as the difference between mean annual potential evapotranspiration and precipitation. Groundwater recharge (GW) is derived as the minimum of the monthly runoff climatology during each of the time periods. The minimum cutoff value (0.000001) is used to avoid negative values. Flood indicator (WET) represents the 98th percentile of monthly runoff time series during each of the time periods, while drought indicator (DRY) is calculated as the 5th percentile of annual runoff time series during each of the time periods. Note that each metric may be derived on a different time scale (monthly or annual).

$$CMI = \frac{PRC}{PET} - 1,\ if\ PET \geq PRC\ (dry\ condition)$$

or

$$CMI = 1 - \frac{PET}{PRC},\ if\ PRC > PET\ (wet\ condition)$$

As discussed in Section 2.2, a water-stress index (WSI) was calculated for each county as the ratio of annual water withdrawal over water supply. Here, we use the estimated runoff from the abovementioned procedure to represent water supply in calculating the water stress index (WSI). For county level water withdrawals, we have extracted data from the U.S. Geological Survey (https://water.usgs.gov/watuse/data) for corresponding year. Added data for surface freshwater withdrawals and groundwater freshwater withdrawals to determine total freshwater withdrawals. For the combinatory metric (discussed in Section 2.2 and Table 1), we employ an average WSI from 2010 and 2015. The total freshwater withdrawal for 2010 and 2015 is averaged and the runoff for 2010 and 2015 is also averaged, and the ratio of withdrawal/runoff is then taken to obtain WSI.

Water Quality is based on the EPA Water Quality Index. Lower values represent better quality and higher values represent worse quality. The EPA created the Water Quality Index from 6 data sources: the WATERS program database, Estimated Use of Water in the United States, the National Atmospheric Deposition Program, the Drought Monitor Network, the National Contaminant Occurrence Database, and the Safe Drinking Water Information System. The data can be downloaded from https://edg.epa.gov/EPADataCommons/public/ORD/CPHEA/EQI_2006_2010/ and an overview of the Environmental Quality Index is available at https://www.epa.gov/healthresearch/environmental-quality-index-eqi#overview.

A.4 Demographics

The demographic data included on the SESRT platform is obtained from a variety of sources. We provide data on total population, population under 18, population over 65, non-white population, and population below poverty level. These data are based on the 2019 U.S. Census survey – and available at: https://api.census.gov/data/2019/acs/acs5/variables.html. We also provide the corresponding estimate of population density from the total population (in 2019) divided by the area of each county. Another variable provided on the SESRT platform is the unemployment rate. The data is available through the U.S. Bureau of Labor Statistics (https://www.bls.gov/lau/), and we have extracted the data for 2019. The unemployment rate is calculated as a percentage of "employable population" and combines information from the current population survey, current employment statistics, as well as the state unemployment insurance systems (to obtain estimate of employable population). The SESRT platform also provides statistics on the rate of homelessness. The metric is provided as the number of people experiencing homelessness per 10,000 people. We estimate this by taking the statistics of total number of people homeless (only at the state level) provided by the U.S. Department of Housing and Urban Development's Office of Development and Research and divide that by the Census Bureau's total population. This estimate was obtained using data from 2019.

A.5 Human and Environmental Health

We provide various mortality rates across various age groups that have been obtained from the Centers for Disease Control and Prevention.

- Deaths, ages 0-5
- Deaths, ages 5-25
- Deaths, ages 25+
- Circulatory Deaths, ages 25+
- Respiratory Deaths, ages 25+
- Death Rate, ages 0-5
- Estimated Death Rate, ages 0-5
- Death Rate, ages 5-25
- Estimated Death Rate, ages 5-25

- Death Rate, ages 25+
- Estimated Death Rate, ages 25+
- Circulatory Death Rate, ages 25+
- Estimated Circulatory Death Rate, ages 25+
- Respiratory Death Rate, ages 25+
- Estimated Respiratory Death Rate, ages 25+

The data is available at https://www.cdc.gov/nchs/nvss/deaths.htm and we have provided the data for 2016. For several counties, the age-specific, cause-specific mortality data that result in a small number of deaths are omitted, due to privacy constraints. We estimate death rates for such counties based on state-level averages. As discussed in Section 2.2, we also provide an estimate of the population weighted average of the exposure to airborne particulate matter (μg/m3). Gridded concentrations of fine particulate matter (PM2.5) (Di *et al,* 2021) are combined with gridded population data (CIESIN, 2018) to provide an estimate of the annual average level of PM2.5 experienced by the population of each county in the US.

In addition to human health information, we also provide data on environmental health, sustainability, and biodiversity. Currently we include data on critical habitat obtained from the U.S. Fish and Wildlife Service Threatened and Endangered Species Active Critical Habitat Report, and it is provided as the percentage of land in a county that is considered critical habitat. We represent this as the percentage of the total county area. In addition, we include information on wildfire risk based on the mean burn probability USDA and the U.S. Forest Service (available at: https://wildfirerisk.org/download/). The data is provided at higher spatial resolution than our visualization, and we aggregate the data to obtain a county-level value. The data provided on endangered species is obtained from the Global Biodiversity Information Facility (GBIF - https://www.gbif.org/occurrence/download/0089477-210914110416597). However, the endangered species counts in the data obtained only include plants and fungi. Further work toward a more comprehensive treatment of these biodiversity related metrics is ongoing and will expand upon this coverage.

A.6 Infrastructure

Currently, our representation of infrastructure is provided by graphical overlays with any selected metrics that are displayed at the county-level scale. Among these overlay options includes electric power transmission lines. This is based on shapefiles obtained from the Homeland Infrastructure Foundation-Level Data (HIFLD – at https://hifld-geoplatform.opendata.arcgis.com/datasets/electric-power-transmission-lines). To reduce latency in the graphical display we provide transmission lines at the Level 2 (230-344kV) and Level 3 (>= 345kV). Underground transmission lines are included where sources were available. Similarly, we have also extracted data from the Natural Earth data portal (https://www.naturalearthdata.com/downloads/10m-cultural-vectors/) in order to provide overlays for major roadways (that include major interstate highways) and railways. We have also obtained data from the U.S. Army Corps of Engineers National Waterway Network (downloaded from https://usace.contentdm.oclc.org/digital/collection/p16021coll2/id/3798/) to provide overlay options for major waterways (or "marine highways") used in the transportation of raw materials and goods. For the major waterways data, the overlay option is further separated into sub-categories of: coal and petrol; food; crude materials, chemical, manufacturing, and "other" to illustrate the tonnage of goods shipped.

A.7 Climate Opinions

We have collected information (at the county level) from the Yale Program on Climate Change Communication. Specifically, we have gathered data from their survey on climate change beliefs, risk perceptions, and policy preferences (e.g. Howe *et al.*, 2015). For the SESRT platform, we have provided results (% of county population) on the survey's positive (or "yes") responses to the following:

- Discuss global warming at least occasionally
- Support requiring fossil fuel companies to pay a carbon tax
- Support setting strict CO_2 limits on existing coal-fired power plants
- Agree that your local officials should do more to address global warming
- Agree that your governor should do more to address global warming
- Agree that congress should do more to address global warming
- Agree that the president should do more to address global warming
- Agree that corporations and industry should do more to address global warming
- Agree that citizens themselves should do more to address global warming
- Support regulating CO_2 as a pollutant
- Support requiring utilities to produce 20% electricity from renewable sources
- Support expanding offshore drilling for oil and natural gas off the U.S. coast
- Support drilling for oil in the Arctic National Wildlife Refuge
- Support funding research into renewable energy sources
- Support providing tax rebates

- Hear about global warming in the media at least once a week
- Agree that global warming should be a high priority for the next president and Congress
- Agree that schools should teach about global warming
- Agree that global warming is happening
- Agree that global warming is caused mostly by human activities
- Agree that most scientists think global warming is happening
- Are worried about global warming
- Think that global warming will harm me personally
- Think that global warming is already harming people in the US
- Think that global warming will harm people in developing countries
- Think that global warming will harm future generations
- Think that global warming will harm plants and animals
- Think a candidate's views on global warming are important to their vote
- Think that global warming is affecting the weather in the United States

These and other data from the survey are available at: https://climatecommunication.yale.edu/visualizations-data/ycom-us/. We have collected and provide the data obtained from the 2021 results.

Appendix B. Software Design and Data Procedures

Evaluate use cases

We based our software design off the website requirements. Initially, these were:

- Display a small number of county-level datasets in the United States
- Add datasets together to show their weighted average
- Allow adjusting the weighted average with a slider

Compare options

To simplify comparison, we categorized options as services, frameworks, and libraries.

	Service	Framework	Library
Description	Pre-made data visualization graphical editor	Large software package that creates the entire website	Small software package that can help with data visualization
Examples	Tableau, ArcGIS Online	R Shiny	d3, react, OpenLayers, Mapbox, Leaflet
Pros	Fastest development time	Medium development time	Most versatile Easier for software engineers to modify
Cons	Least versatile Must pay monthly fees to use	Limited versatility	Slowest development time

We investigated options from each category. Tableau took more than 1s to load our shape files, and did not make it easy to combine datasets and adjust weighted averages. R Shiny didn't have a large developer following, and thus the community support wasn't as good as the other more in-depth software libraries. We settled on d3 and react, because they had good community support and a large following, which made development in them easier.

Decide on software design for version 1

To simplify development and maintenance, version 1 was a frontend site with no backend. We used a topojson command line utility (https://github.com/topojson/topojson-simplify) to reduce the size of our map to under 1MB, and store our datasets in a single csv file that's small enough it could be preloaded with the site. We wrote it in typescript to reduce the likelihood of runtime errors. We used d3 for data manipulation, loading and react for rendering.

Redesign version 2 to accommodate more data

We needed to load at least 10x the data when we added time-series data, which would take too long to load in one go on a static site. We stored the data in a PostgreSQL database so we could query small slices of the data on-demand. To load data from the database, we used a backend binary server written in Rust with the actix-web framework. Rust allowed us to deploy our service using only the binary file (as opposed to a java which would require a whole runtime) while having more memory and concurrency safety than C++. We used GitHub actions to test and build continuously, to reduce development time.

Data Procedures

Because the data came from many sources, we decided on a standard format with which to present and combine the data. Many of the data sources had different sets of counties they reported on including missing counties, combined results for multiple counties, unpopulated areas such as forest aeras, etc. Therefore, we the list of counties reported by the Census Bureau (available at: https://www.census.gov/library/publications/2011/compendia/usa-counties-2011/file-layout.html#part03) and aligned all other data sources to fit this list. Most missing values were reported as such, unless there was a reasonable or necessary alternative. In instances where the average of several counties was given, that average was assigned to each county individually. For data where there were significant missing entries, relevant and widely used methods of estimation were used to assign values to those counties. All the source data and the parsing methods are open source and available for download (see Appendix A for further details).

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