Emission Explorer

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Project Objective:

Our objective is to identify a visualization and data-driven approach that will facilitate strategies to achieve the United States Federal Government's goal of reducing Greenhouse Gases (GHGs) and achieving carbon net neutrality by 2050 (United States Department of State and United States Executive Office of the President, 2021). This federal goal is currently being implemented through laws like the Inflation Reduction Act, improved passenger vehicle standards, and Environmental Protection Agency regulations on gas and oil. Our focus will be on one of the major contributors to GHGs: energy generation and consumption. Our project will help stakeholders to identify additional potential for improvement in areas like transitioning to renewable energy sources, research on modern technologies to achieve lower emissions, and support collaborative learning by identifying success in similar areas and socio-environmental development by identifying demographic split and correlation.

Multiple stakeholders across various sectors contribute to achieving carbon neutrality goals including governing bodies, non-government climate-focused organizations, academic researchers, citizens, and corporations such as Google, (Sofia O'Connor, 2019).

Problem Statement:

Identify the geographical areas with the least renewable energy and forecast future statistics using an analytical approach to create tools for visualization of the eGRID dataset to assist stakeholders with decision-making for continuous improvement.

Dataset Overview:

Every year, the Clean Air Market Division (CAMD), Office of Atmospheric Programs (OAP), and U.S. Environmental Protection Agency (EPA) release The Emissions & Generation Resource Integrated Database (eGRID). eGRID is a comprehensive source of data on the environmental characteristics of all electric power generated in the United States. This dataset includes electricity generation by resources (fuel), emission percentage for various GHGs, and classification into renewable and non-renewable resources. The latest edition of this dataset includes demographic data based on region from the census dataset. Currently, the dataset is available for the years 1996 to 2022. The published data is an Excel document with no interactive tool available and has the limitation of the most recent data being over a year old.

Methodology:

The first step of our approach is to create a visualization and interactive tool using a USA map for data exploration. This tool will focus on exploring factors like greenhouse gas (GHG) emission, energy generation, population, and energy consumption. This tool will also explore identifying the highest contributors for renewable generations, non-renewable generations, and GHG emissions. To achieve this visualization, we will use tools like Excel for data formation and compiling, python for data cleaning, and Tableau for building graphics. We will focus on best practices in User-Centered Design as explored by research from Academic Cartography (Tsou, 2013) and highlighting point features from research from the Cartographic Journal (Gedicke & Haunert, 2023).

Previous energy-related research around GHG emissions done in Ghana, Iran, India, and Libya utilized time series-based models to predict future emissions (Yen Adams Sokama-Neuyam, 2023), (Hosseini, Saifoddin, Shirmohammadi, & Aslani, 2019), (Kumari & Singh, 2023), (El-Mallah & Elsharkawy, 2016). We will use a similar approach to forecast future data as our data has been trailing for over a year. Therefore, our second step is to use different time series models using Python like ARIMA, Moving Average, GMM, and linear models to do the emission predictions for the next 5-10 years. Another method that we may pursue is Ridge Regression as a fusion of time series prediction and variables regression (Li Y. , 2020). We will evaluate models using different metrics like mean absolute percentage error, mean square error, and root mean square error to pick the best-performing models. The advantage of using time series models is to help us identify trends and patterns in the dataset which is especially useful to design strategies and policies. The innovation in our model will be to compare the individual states to regions to see if using regional data the state emissions can be reduced.

In step three of our project, we will explore the relationship between demographic factors, emissions, energy generation, and consumption, and our innovation will be our visualization of these factors. This step is inspired based on the article 'Demographic change and carbon dioxide emissions' which explores the historical IPAT equation i.e. I=PxAxT where I stands for environmental impact, P stands for population, A stands for consumption and T stands for impact per consumption (Brian C O'Neill, 2012). In an article by Grossman, he reviews the shape of the relationship between income and environmental harm called the Environmental Kuznets curve (EKC) (Grossman, 2010). Other authors have proposed different shapes other than his U-shaped curve such as a linear relationship or an N-shaped relationship (Li & Lin, 2015), (Nassani, Aldakhil, Abro, & Zaman, 2017). These results will help stakeholders identify areas that need social and cultural awareness related to energy habits and environmental changes and show the location on the EKC curve.

Evaluation:

One benefit of providing visualizations and predictive analytics is that decision-makers can better understand the dynamics of energy demand and social implications, leading to more informed policy decisions (Walker, 2014). Also, being on track for carbon neutrality goals aligns with international agreements like the Paris Treaty, fostering global cooperation towards a common environmental objective.

Some of the risks of relying on historical data for forecasts are that they may not fully capture the complexities and nuances of future emissions patterns, leading to inaccurate forecasts. There is also a risk that the chosen time series forecasting models may not accurately predict future greenhouse gas emissions due to unforeseen events or changes in policy.

The timeline set out for a sustainable energy landscape is the year 2050. However, across the United States, there are different rates of adoption of different energy technologies. For example, in the Pacific Northwest, there has been a rapid implementation of wind energy generation due to government incentives like a corporate tax credit of 50% of eligible project costs (Daim, Amer, & Brenden, 2012). While not all sources of energy are as available as wind in the United States, some other states are uniquely suited for other types of energy generation like hydroelectric and solar. These other types of energy could also be used to support 80-85% of current energy replacement by 2030 and complete replacement by 2050 (Jacobson, et al., 2015).

Acquiring additional datasets beyond eGRID may involve costs, but as much energy information is publicly available, expenses revolve around time and possibly computing.

Conclusion:

In a study from 2018, analyzing individual state contribution to carbon emissions, the impact of half of the United States cooperating in this study's plan would result in a 68% decrease in carbon reduction (Galan-Martin, et al., 2018). With additional information on regional neighbors' renewable energy strategies, this number could be even higher. Also, global GHG emissions are already being measured for the EDGAR 7.0 Database. (Directorate-Generate for Climate Action, 2023). So, any results from decreased emissions will be reflected in this EU database and will promote global cooperation in climate initiatives. The biggest impact is that successful policy implementation will assist in slowing down climate change.

The midterm "exam" will be the progress report due on April 1st and the final "exam" will be a combination of the final poster presentation and the final report. Progress will be measured on a group Excel chart that will be kept up by each of the members of the team and will be measured by the deliverables being turned in before the due dates for the assignments listed in Table 1.

Task	Start Date	End Date	Team Members
Form Project Team	1/12/2024	1/17/2024	Sharvari with input from rest
Decide on Topic	1/17/2024	1/30/2024	All
Data Collection	1/17/2024	1/30/2024	All
Proposal Document	1/30/2024	2/25/2024	All
Proposal Presentation Slides and Video	2/25/2024	2/28/2024	Alicia with input from rest
Data Preparation and Cleaning	3/1/2024	3/5/2024	All
Model Creation	3/5/2024	3/15/2024	All
Develop Plan for Visualization	3/15/2024	3/22/2024	All
Progress Report	3/22/2024	3/29/2024	All
Final Report	3/29/2024	4/19/2024	All
Poster	3/29/2024	4/19/2024	All

Table 1: Task List: All team members have contributed a similar amount of effort.

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