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A Visual Analytics Framework for Renewable Energy Profiling and Resource Planning

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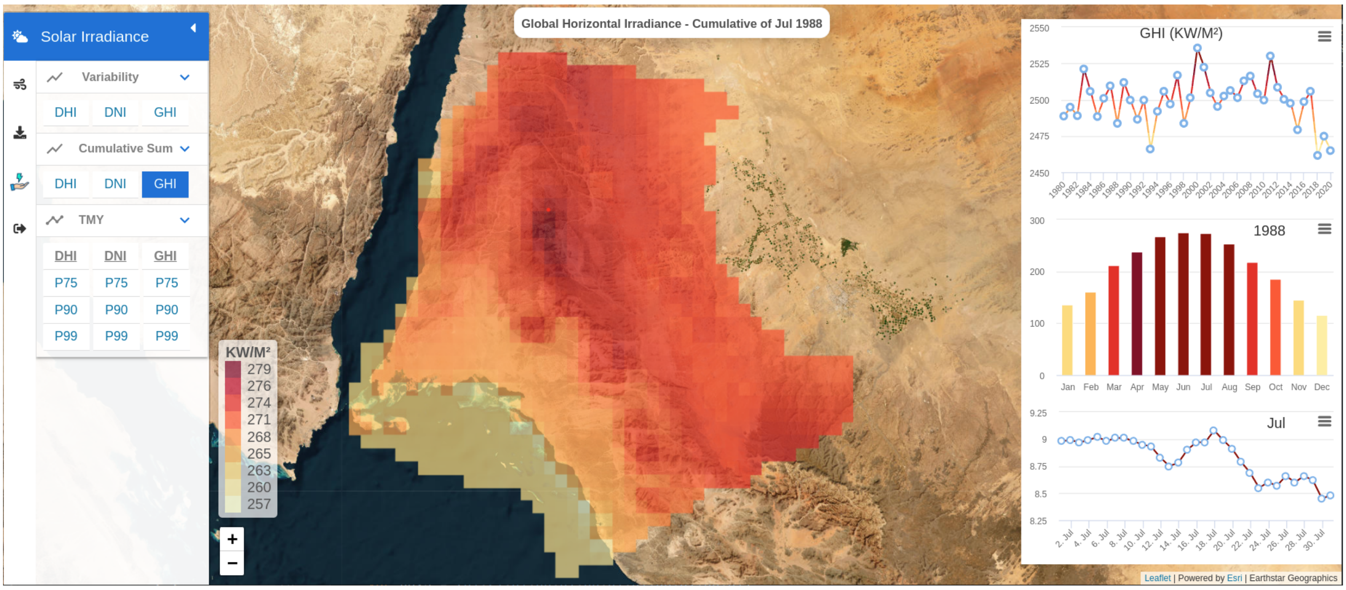

Figure 1: *A visual analytics framework for exploring the solar and wind power parameters for renewable energy resource planning. Map view is showing Global Horizontal Irradiance (GHI) for a given region. Yearly, monthly and daily cumulative sums are shown in linked plots.*

Abstract

Renewable energy growth is one of the focus areas globally against the backdrop of the global energy crisis and climate change. Energy planners are looking into clean, safe, affordable, and reliable energy generation sources for a net zero future. Countries are setting energy targets and policies prioritizing renewable energy, shifting the dependence on fossil fuels. The selection of renewable energy sources depends on the suitability of the region under consideration and requires analyzing relevant environmental datasets. In this work, we present a visual analytics framework that facilitates users to explore solar and wind energy datasets consisting of Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI), Diffusive Horizontal Irradiance (DHI), and Wind Power (WP) spanning across a 40 year period. This framework provides a suite of interactive decision support tools to analyze spatiotemporal patterns, variability in the variables across space and time at different temporal resolutions, Typical Meteorological Year (TMY) data with varying percentiles, and provides the capability to interactively explore and evaluate potential solar and wind energy equipment installation locations and study different energy acquisition scenarios. This work is conducted in collaboration with domain experts involved in sustainable energy planning. Different use case scenarios are also explained in detail, along with domain experts feedback and future directions.

CCS Concepts

• ***Human-centered computing*** → ***Visual analytics;*** • ***Applied computing*** → ***Environmental sciences;***

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1. Introduction

There is a great global push toward renewable and clean energy sources, and there are many drivers accelerating these developments such as climate change, increasing fossil fuel prices, and improvements in technology. Many countries are developing energy plans to increase the contribution of renewable energy sources in their energy mix. Energy planners and policymakers are increasingly incorporating sustainable energy generation options in their energy plans for large-scale infrastructures and associated development projects. Incorporating these sustainable energy resources in the overall energy mix and ensuring an uninterrupted power supply requires extensive planning, exploring diverse scenarios, evaluating feasibility, and identifying suitable regions for energy harvesting. The question of where to install the large-scale renewable energy farm can be addressed by exploring the historic and geographical prominence of various locations in the domain of interest.

Analysts use data-driven simulation models [DDL-19a] to address these challenges and make calculated decisions. They need to characterize sustainable energy resources by conducting spatial and temporal assessments at varying resolutions. They also need to explore variability in simulated energy sources at different temporal scales, and access other linked statistical measures for any selected site. Spatial and temporal analysis reveals possible sites for energy-generating infrastructure like solar thermal plants and wind turbines. Analysts use derived measures such as Typical Meteorological Year (TMY) and linked statistics to improve estimation and operational strategies.

In this work, we present a visual analytics framework that can facilitate interactive exploration, and visualization of solar and wind energy profiles of reanalysis data of Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI), Diffusive Horizontal Irradiance (DHI), and Wind Power (WP) during 1980 – 2020. The reanalysis datasets presently being used are generated by assimilating observations from a variety of sources, including surface stations, radiometers, satellites, and other instruments, into the Weather Research and Forecasting (WRF) solar system [MCK13, RBABHT*20, LWT*21]. The generation of the reanalysis data using the observation stations along with the validation is described in detail by [DDL*19]. The framework enables spatiotemporal exploration of generated renewable energy outputs and other derived datasets through a suite of linked visualizations. The framework gives users the ability to explore TMY, Variability, and historical changes that occurred at any selected location to figure out the best potential locations to extract maximum renewable energy. Also, the total estimated power generation, if installed at the selected location, can be matched against the energy demand requirements taken from the user.

2. Related Work

The smart city concept is becoming ubiquitous [HJ*22]. Data visualization and analytics play an efficient role in understanding the data generated by these smart cities, finding underlying patterns and insights, and eventually assisting the decision-makers [CMJBGMG22, CLW*18]. Renewable energy profiling is becoming one of the important focus areas due to the global energy crunch and a need to focus on green energy [RRR22, UNC23, GGW*19, JPNGE12, AE*19].

In the recent past, various tools have been proposed to analyze energy datasets obtained from various sources and then do demand planning based on predictions of the data [KKK*14]. Carli et al. [CAD*15] designed a dashboard and decision-making tool to efficiently analyze energy data for environmental sustainability. Adepetu et al. [AGA*12] proposed a sustainable energy decision support system to analyze a city energy system. Chen showed in [Che23] how visualization can effectively help analyze and forecast energy data. Carli et al. [CDDP14] proposed a decision management system for analyzing the renewable energy data for a smart city. Moghadam et al. [TCM*19] designed a visualization system to help urban planners in energy analysis. Hamad et al. [HAA21] recently proposed a simulation of the renewable energy demands for the futuristic Neom city of Saudi Arabia. Some work has also been done in the areas of residential energy data analysis, modeling, and forecasting [GAAZD20, TVS*22]. There is also a recent trend of using deep learning and machine learning techniques to accurately model and predict energy demand [SRA21, GN19, Vij22]. Our work differs from the above-mentioned papers as our presented framework is designed to cater to the specific domain scientist's requirements that these tools do not provide.

3. Tasks and Requirements Analysis

This work was completed in close collaboration between energy planners, atmospheric domain scientists, and visualization experts. We first examined the needs of sustainable energy resource planners and decision-makers. We identified the solar and wind energy profiles needed to be built based on available datasets. The simulation models and observational datasets utilized in this investigation are described in Section 5. Later, the functional task requirements were collected in discussions focused on how the domain experts envision the analysis workflows for harvesting sustainable energy resources. These requirements were gradually refined in multiple iterations and discussion sessions among the collaborators. These interactions yielded the following tasks and design requirements:

T1: Explore energy concentrations and linked statistics for solar and wind energy datasets in a geospatial environment

T2: Spatiotemporal exploration of the reanalysis datasets (raw and derived) of solar and wind energy variables.

T3: Selection, filtering and drill-down capabilities supporting spatiotemporal exploration of solar and wind datasets.

T4: Explore annual, monthly, daily, and hourly solar and wind energy variations for any selected location

T5: Explore cumulative sums of solar and wind energy variables across space and time at varying temporal resolutions.

T6: Explore Typical Meteorological Year (TMY) data for solar and wind variables at varying percentiles across space and time.

T7: Build and explore different energy generation scenarios through placement of solar installations.

4. Visual Analytics Environment

Our visual analytics environment consists of multiple linked visualizations (Figure 1). These visualizations include a geospatial map view that lets users interactively explore and analyze solar (DHI/DNI/GHI) and wind energy data (T1, T2) on a grid-ded map. Through selection and filtering options related to these views (T3, T4, T5, and T6), users may load and analyze variability, cumulative sums, and Typical Meteorological Year (TMY) data (P75, P90, and P99 percentiles) relevant to solar and wind energy variables. After selecting a variable, the map view displays a relevant color-coded spatiotemporal dataset. Users may explore spatial data in the map view and scroll through time at different temporal granularities. After selecting the region of interest, a linked stack of time series visualizations displays energy data at annual, hourly, monthly, and hourly scales along with variability statistics. Time series visualization options update the map view (T3) since both views are connected.

This functionality allows interactive multi-dimensional data searches and diverse analytical workflows. Users may examine trends and study odd data variations, and the interactive drill-down functionality helps domain scientists and decision-makers evaluate solar and wind factors at multiple levels of detail and compare places of interest. Variability, cumulative sums, and TMY datasets for solar and wind energy are supported. Figure 1 illustrates a user selecting GHI solar irradiance. The map view displays cumulative sums for July 1988, which the user chose in the time series view, along with annual, monthly, and daily time series data. Users may interactively place solar panels on the map and estimate monthly energy production in the scenario-building view (Fig. 4). System-supported solar energy characteristics determine panel placement. Energy generation thresholds may also be used to filter grid cells on the map with required energy generating potential. Users may also enter a demand curve estimating monthly energy needs. The linked time series shows energy production and demand curves along with surplus/deficit information as a bar graph. This interface lets users create and examine data-driven energy-generating scenarios (T7).

5. Data and Methodology

We have used an assimilative configuration of the WRF Solar model [MCK13, RBABHT*20, LWT*21] to generate Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI), and Diffusive Horizontal Irradiance (DHI) datasets for a period of 40 years (1980 - 2020). We ran the simulation model on a high-performance computing platform (SHAHEEN supercomputer [HKF*15]). Observations from 46 ground-based radiometer observatories across the Arabian peninsula are considered over a period of 4 years to minimize the modeling uncertainties and the accuracy of the modeled data as elaborated by Dasari et al. [DDL*19]. The datasets with a spatial resolution of 5km x 5km and temporal resolution of one hour, having size around 158 GB is produced as an output by the reanalysis. We derive further datasets representing cumulative sums, variability, and Typical Meteorological Year(TMY) from these datasets. To represent a synthetic year for the NEOM region, Typical Meteorological Year (TMY) values are calculated for each grid point. The daily average values are determined using the median (Percentile 50) and pessimistic values (Percentile 75, 95, and 99). Percentiles such as 75, 90, and 99 are generally used to obtain a conservative estimate that is close to the lowest value over time. The variability is also calculated along with TMY to aid in better estimation and operational planning. The TMY and Variability values provide a better understanding of the potential energy that can be harnessed from a solar plant installed at a specific location.

$$E = A * r * H * PR,$$

(In simple terms, *Solar power = Irradiance x Efficiency x Area*) where E is the computed energy (Watts), A is the total area covered, r is the solar panel yield, H is the average solar radiation and PR is the performance ratio. In the present study, we have used the standard performance ratio of 0.75 and fixed the solar panel to 15.6, considered ideal under Standard Testing Conditions [BPE17].

Similar to TMY for solar power, TMY for wind power is calculated based on long-term historical data. The present framework uses hourly wind speed data for the same period (1980 - 2020). The data includes wind speed, wind direction, and air density, which are used to calculate the power output of a wind turbine. Once the TMY data is obtained, it can be used to estimate the annual energy production of a wind turbine at the location of interest. This information is useful for energy planning for a given region. The following equation is used to determine the amount of electrical power that can be generated by a wind turbine:

$$Power = 0.5 * P * A * V^3 * Cp,$$

where Power is the output power in Watts, P is the air density (kg/m³), A is the swept area of the turbine blades (m²), V is the wind speed (m/s), Cp is the power coefficient of the turbine, which is a measure of its efficiency in converting the wind's energy into electrical power. The value of Cp typically ranges from 0.25 to 0.45 for modern wind turbines [CRSMLR20, JPJ13].

6. Implementation Details

The underlying framework used to build this visual analytics environment consists of a multitiered architecture. The bottom-tier is the 'data generator', which executes physical models on an HPC platform (SHAHEEN) to generate forecasts. The output files are transferred to the 'analytics and visualization' server. This server contains the backend core application (containing all the algorithmic code) and visualization dashboard components. Different application services accessible via RESTful API can also be deployed on the server. The backend core is primarily implemented using Python, Numpy, Ferret, Climate Data Operator, NetCDF4, and MySQL. Server configuration consists of Flask, gunicorn, and NGINX. Visualization dashboard components are built using Leaflet, D3, Highcharts, Angular, Materialize, JavaScript, HTML, and CSS.

7. Use Case Scenarios: Solar and Wind Energy Harvesting

Installing large solar plants depends on several factors, including the distance from the demand site, availability of radiation values above certain thresholds, terrain constraints, battery capacity, dust losses, temperature variations, and wind anomalies. To simplify decision-making, the present visual analytics framework enables users to investigate high solar and wind energy yield intensity

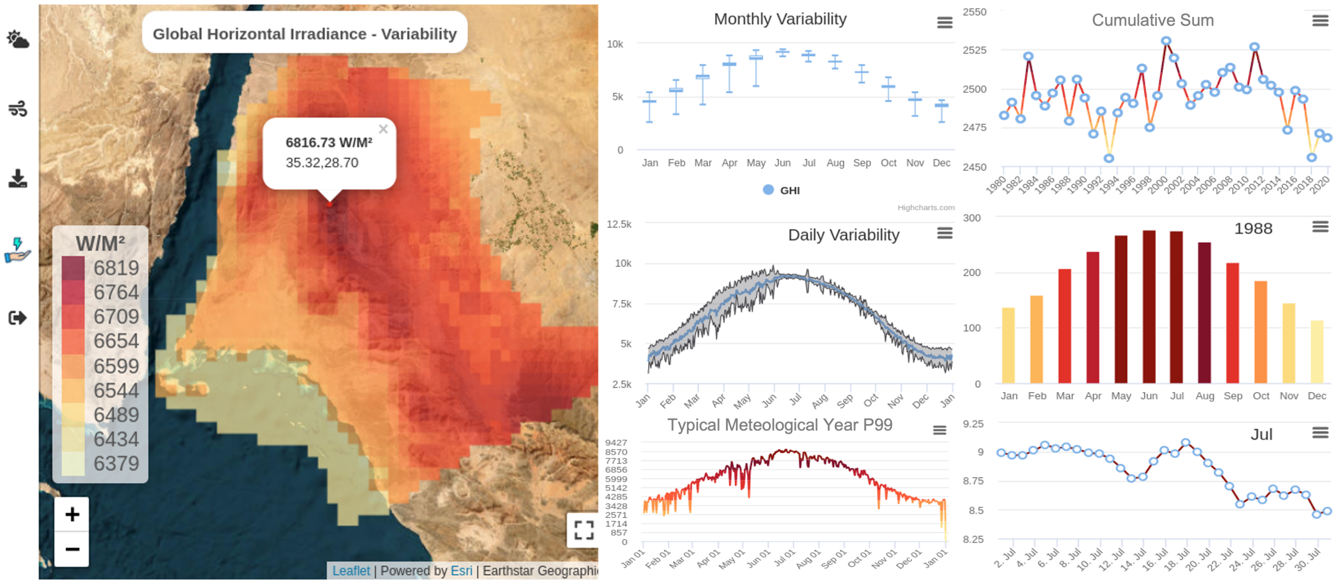

Figure 2: *Examination of the prospective site for solar plant installation. (Left) demonstration of spatial intensities over an interactive map. (Center) monthly and daily variability of the GHI values based on historical data along with the Typical Meteorological Year values. (Right) Exploring historical GHI values at yearly, monthly, and daily timescales.*

regions by exploring the cumulative sum of concentrations overlaid on an interactive map. However, it's important to examine the variability and TMY at 90 and 99 percentiles at the selected locations which gives the standard deviation based on historical data, while TMY provides the percentile value closer to the minimum. For large solar plant installations, TMY at 95 or 99 percentiles is primarily used as it guarantees minimum radiation values.

The system can derive estimated power generation by interactively placing grids of panels at the selected locations (Section 5). The framework also enables users to weigh the generated power against hypothetical monthly demand requirements, allowing them to determine the number of grids needed to meet their requirements. Analysis of the energy potential at a particular location is presented in Fig 2. Overall, this approach can help optimize the placement and performance of solar plants and improve the efficiency of renewable energy resources. After identifying potential locations based on the cumulative energy concentration of the region (**T1**), further filtering can be performed by considering factors such as variability and TMY values at the 99 percentile for the selected locations (**T4, T6**). At the locations with minimum variability and maximum TMY values, users can simulate virtual solar panels and calculate the average power generation for 1000 individual panels (Fig 4). Furthermore, users can add more panels and compare the expected power generation against their demand (**T7**). The current system for evaluating wind power potential enables decision-makers to compare different areas and determine where wind energy farms would work best. The process for identifying suitable locations is similar to that used for solar panel placement. The analysis of wind power potential starts with a look at how wind power concentration is spread out across the whole region. Fig. 3 compares the wind power potential of the western region against the eastern region. This shows that the area along the Gulf of Aqaba up to Tiran Island is more suitable for harvesting wind energy. The values of variability and TMY are looked into to learn more about wind power patterns.

8. Domain Experts Feedback

We collected feedback from two domain scientists (not co-authors) working in academia. One is an expert on materials and solar cell design and the other works on manufacturing technologies for energy harvesting and generation. Initially, we demonstrated the system to the experts showcasing the features and complete functionality. Then they explored the system on their own, working on different use case scenarios.

In their feedback, they mentioned that overall the dashboard provides an efficient way to explore long-term historical datasets of solar radiation and wind power. Exploring typical meteorological year and variability is especially helpful for obtaining a more accurate estimate of how much power can be harvested at each location of the region of interest. The system would be even more powerful when parameters such as wind speed, temperature, rainfall, and dust storm information are interactively varied for carrying out sensitivity analysis. Also, from the stakeholder's point of view, the capability to select from multiple solar panel configurations would result in better planning for installation and mass procurement.

9. Future Directions

Once a solar plant is established, the operational short-term forecast becomes crucial for planning oversupply and undersupply. To achieve this, the system can utilize Artificial Intelligence (AI) techniques to analyze low-level, mid-level, and high-level cloud cover

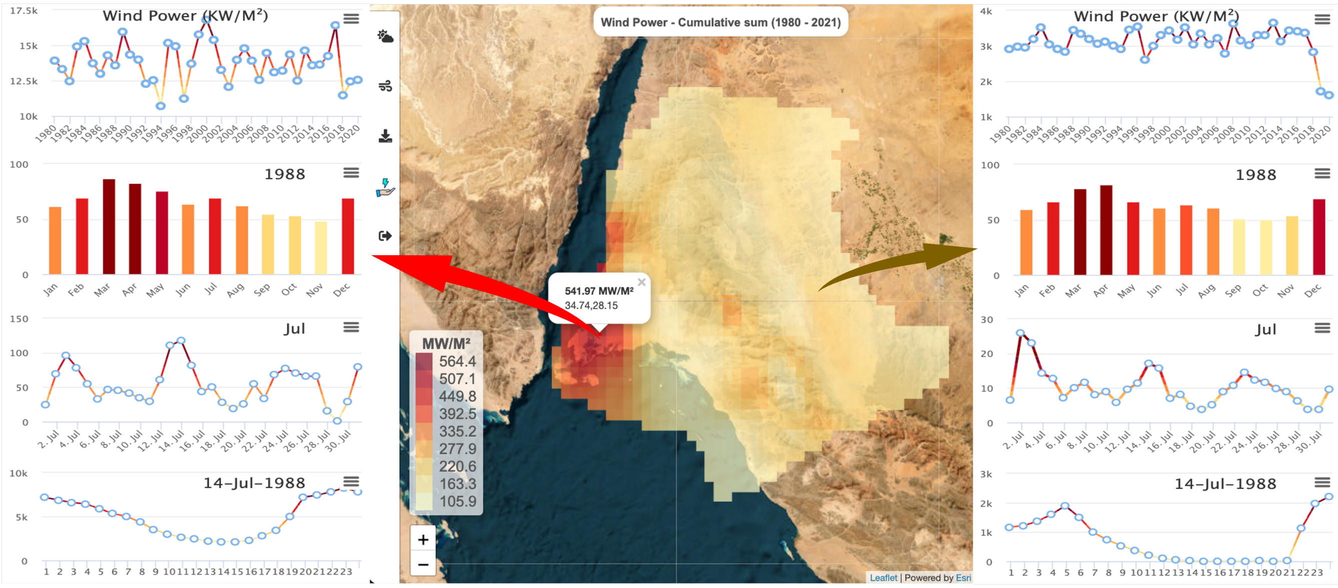

Figure 3: *Comparison of the historical wind power potential along the Gulf of Aqaba and the eastern region of NEOM.*

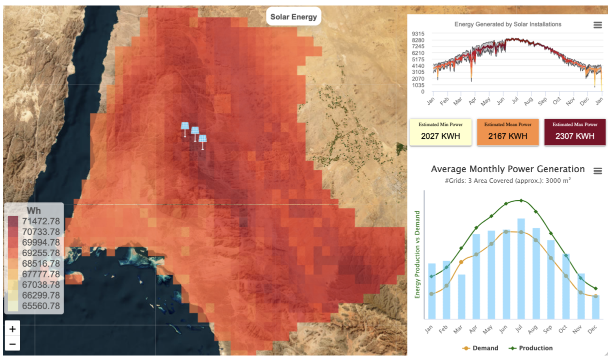

Figure 4: *Interactive placement of solar panels. Linked time-series views are showing (a) the estimated energy generated by the selected solar panel on the map (top right), and (b) the Average monthly power generation, providing a comparison between hypothetical energy demand and estimated production (bottom right).*

data, in addition to other weather data, to generate more accurate predictions of energy generation. This will enable energy planners to better manage the gap between supply and demand, ensuring a reliable and stable power supply. Integrating deep learning architectures like convolutional LSTM can help learn spatial and temporal patterns, and can facilitate planning for solar droughts.

The future version of the system will parameterize solar panel yield, wind speed, and surface temperature for estimating energy generated by specific solar panels and wind turbines. This will provide a simplified model for estimating energy generation potential at different locations, allowing planners to identify suitable sites for solar plant installations. We will integrate a database of solar panels that would enable users to make multiple energy generation plans satisfying multiple criteria. Also, we will extend the visualization framework to enable users to manage and compare a large number of scenarios. We will further add support to create scenarios for wind energy infrastructure as well. We will evaluate the impact of any infrastructure around the planned solar and wind energy installations and how it may affect potential energy yield. we also plan to conduct a more comprehensive user evaluation focused on practical sustainable energy planning scenarios.

10. Conclusions

The process of profiling and planning for optimal energy generation is facilitated by the presented visual analytics framework. By analyzing data at the 99th percentile and studying its variability, it is possible to estimate the potential solar power and identify optimal locations for energy harvesting within a specific area. The statistics related to the reliable reception of energy are drawn, forming the basis for plant installations. The ability to interactively explore solar and wind energy related data and visualize it through multiple linked visualizations enables users to build and explore different data-driven energy generation scenarios, allowing for more efficient assessments and decision-making. Overall, this work emphasizes the potential benefits of leveraging data analysis and visualization tools to optimize renewable energy production and supports efforts to transition to a more sustainable energy future.

11. Acknowledgments

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