2023

Distributed Energy Infrastructure Development: Geospatial & Economic Feasibility in Rural West Virginia

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Thesis submitted to the
Davis College of Agriculture, Natural Resources and Design
at West Virginia University

In partial fulfilment of the requirements for the degree of

Master of Science in
Energy Environment

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Division of Resource Economic and Management

Morgantown, West Virginia
2023

Keywords: Distributed Generation; Energy Security; Suitability Analysis; GIS; Multi-Criteria

ABSTRACT

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Energy transition from conventional to centralized power plants, including coal-fired units, is critical for West Virginia's long-term energy and economic future. The socioeconomic downturn in West Virginia was deeply connected with the dependence on the centralized coal industry and the coal economy. Most traditional coal communities in rural West Virginia struggle to maintain economic viability, potentially leading to outmigrations and poor energy resilience. I investigated the possibility of introducing community-sized distributed energy systems in these rural communities to improve energy resilience and accommodate the future transition from centralized coal-generated energy.

My goal was to identify rural regions where distributed energy can be utilized at an optimal cost, thus improving energy resiliency within these communities and positively impacting the economy. This study provided a geospatial modeling approach with Multi-Criteria Decision Analysis (MCDA) and Geographic Information System (GIS) suitability assessment to identify the feasible locations of small-scale distributed generation for wind, solar, and hydropower energies. The net value comparison analysis was conducted utilizing the levelized cost of energy (LCOE) and levelized avoided cost of energy (LACE) to determine the differences in investment costs for each distributed generation type compared with traditional coal-generated electricity.

I expected the spatial analysis results to reveal optimal sites for the specific distributed energy types. I found that wind and solar distributed generation have stronger presences in southern and eastern West Virginia counties, while suitable small hydropower development locations are spread across the state. This study provided insight into future distributed energy and its infrastructure development possibilities in rural West Virginia.

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Key terms and abbreviations

AHP- Analytic hierarchy process

DG- Disturbed Generation

DE- Distributed Energy

DNI- Direct Normal Irradiation

EIA- Energy Information Administration

FSPS- Feasible Small Project Sites

GHG- Green House Gas

GHI- Global Horizontal Irradiance

GIS- Geographical Information System

KWh- Kilowatt-hour

LCOE- Levelized Cost of Energy

LACE- Levelized Avoided Cost of Energy

MCDA- Multi-Criteria Decision Analysis

MWh- Megawatt-hour

NREL- National Renewable Energy Laboratory

NSPS- New Source Performance Standards

SCC- Social Cost of Carbon

Section 1. Introduction

Leading up and beyond the Industrial Revolution, energy and electricity production have been foundational for further development of modern civilizations; they provide the basic needs for communities and settlements to thrive and prosper. The advent of advanced energy production technologies and abundant energy supplies through the industrial revolution led to the fall of old societies and the rise of new ones in the early 20th century (Wrigley, 2013). Energy production, economic viability, and community development are correlated strongly with each other (Cabraal, 2005). The United States' dominance and security in energy production have fueled the country's economic growth and manufacturing superiority since the end of World War II (Johnstone & McLeish, 2020). In the United States, most electricity consumption is generated and coordinated by centralized generation facilities that connect to consumers directly from centralized power grids through regional delivery systems such as transmission lines and powerlines (EPA, 2020). The centralized power grid system has played a substantial role in the development of this country due to the benefits of its extensive energy production and its improved reliability (Manz et al., 2019). Historically, coal, natural gas, and other fossil fuels have been the primary source for these large-scale, centralized generation systems in the US, with coal being the dominant energy source for generating electricity in the past decades (EIA, 2021).

The prominent status of centralized coal energy production and coal-fired power plants, however, have been impacted massively and eventually lost their lead in recent years due to several reasons. Firstly, there has been a market-driven response to lower natural gas prices that have made natural gas generation more economically appealing. The Environmental Protection Agency (EPA) then proposed stricter regulations imposing new requirements under the Clean Air Act, which sets New Source Performance Standards (NSPS) for greenhouse gas (GHG) emissions to reduce GHG and environmental pollution hazards from fossil fuel-fired power plant (EIA, 2016; Campbell, 2013). The aftereffect of these regulations and economic policy changes has critically impacted the coal energy industry and led to a noticeable decline in these traditional energy powerhouses. This decline has resulted in many challenges for existing energy systems and energy infrastructure, especially for West Virginia.

In the past 20 years, West Virginia's coal production has declined significantly due to the aforementioned reasons. As of 2020, West Virginia's total coal production stood at sixty-seven million short tons, less than half of what it was in 2001 and 28% less than in 2019 (EIA, 2021). Consequently, coal mining and coal electricity production jobs in this region have experienced a negative impact, with coal industry employment falling by around 27 percent between 2005 and 2015(Bowen et al., 2018). Most coal communities in West Virginia struggled to maintain their economic viability from reduced employment opportunities and declined income streams (Blaacker & Oliver, 2012). Typically, these communities are rural counties heavily dependent on the coal industry in Central Appalachia and have suffered the most from coal energy production and job losses (Bowen et al., 2018). Meanwhile, the diminishing socioeconomic status due to the decline in the coal industry has also negatively impacted West Virginia’s population (Bell&York, 2010). According to the U.S. Census 2020, West Virginia's population declined by 3.2% from 2010 to 2020, about 59,000 people (Census Bureau, 2020). Essential energy infrastructure maintenance, such as centralized power grid extension and development have also been negatively impacted by poorer socioeconomic conditions due to a heavy dependence on a declining coal industry. Moreover, the rugged terrain and complicated topography of West Virginia tend to isolate rural communities from major infrastructure corridors, making them vulnerable to malfunctions from centralized power grids. Additionally, interruptions to long-distance transmission and maintenance of conventional coal power grids from natural disasters such as flooding and storms have led to increased electricity costs. These energy cost increases and related negative effects on other quality-of-life factors reduce incentives for current residents to remain in their communities (Hazen & Hamilton, 2008).

This decline in West Virginia’s coal energy production and subsequent socioeconomic downturn requires innovative solutions that provide alternative stable energy production and economy vitality to rural communities that have historically relied heavily on coal-based energy. The Distributed Generation

Systems (DG) or Distributed Energy (DE) infrastructures have the potential to be developed in West Virginia's rural regions to support West Virginia's long-term energy transition. A DG is a small-scale electricity generation system based on renewable energies, such as solar, wind, and hydropower, that is located near the end users rather than requiring long-distance transmission lines and powerlines to deliver energy (Ackermann et al., 2005). DG and its on-site production can provide energy stability to rural and remote communities, resulting in cost savings in the transmission and distribution of about 30% of electricity costs compared to existing centralized generations (Pepermans et al., 2005). Transitioning away from centralized coal power grids has the potential to supply sustainable energy production and provide alternative economic development opportunities for West Virginia.

However, energy transition is a challenging process and poses a risk of losing current economic stability, and opportunities provided by coal industries. West Virginia has been a coal-dependent state ever since large-scale mining development began around the mid-1800s (WVGES, 2017). The coal industry has been a staple for West Virginia and a significant part of West Virginia's culture and economy. The existing coal industry infrastructures and centralized energy systems are well established and adaptive to the local community and economy; therefore, it is challenging to completely replace those units even with enough determination and financial support (Blaacker & Oliver, 2012). Despite the increasing renewable energy production in recent years, West Virginia still has heavy presence of coal energy production and consumption. In 2021, approximately 91% of the net electricity generation in West Virginia was generated by coal, according to the US Energy Information Administration (EIA). Renewable energy resources, mostly hydroelectric and wind power, only contribute about 5% (EIA, 2021).

The continued reliance on conventional centralized coal-fired power plants prolongs the socioeconomic downturns caused by the decline of the coal-oriented economy (Bell&York, 2010). This dependence on coal generation can decrease the appeal of modern energy markets in West Virginia as sustainable energy production become increasingly in demand, and thus leave West Virginia vulnerable to adapt in transitioning away from conventional coal energy (West Virginia University, 2020). Over-reliance on centralized coal energy production in West Virginia can also result in a negative feedback loop, with rising electricity costs, poorer quality of life, increased outmigration and inadequate maintenance of energy infrastructure. This cycle can cause long-term negative impacts. Therefore, conducting an integrated spatial and socioeconomic analysis to assess the feasibility of developing sustainable distributed energy in rural West Virginia might prove highly valuable.

The overall goal of this thesis was to investigate the possibility of introducing a distributed generation energy system to West Virginia in hope to further promote transformation from centralized coal energy. We aimed to identify rural regions where it would be geospatially feasible to employ renewable DG systems at an optimal economic cost and, thus, improve energy resilience and positively impact the local economy and quality of life. We recognized the challenges of fully adapting new DG for West Virginia's energy and socioeconomic structure since substantial energy transition requires slow change over the long term. Therefore, we did not aim to replace the centralized coal power plants with DG completely but instead focused on realistic adaptation and improvements from new DG systems. The current ideal DG development would be able to slowly transform and co-exist with the existing centralized energy structure for West Virginia's long-term energy and economic future.

We proposed a novel and realistic energy transformation strategy with the development of community-sized distributed generation infrastructure in West Virginia. Specifically, this thesis intended to identify the types of renewable energy most suitable for potential DG sites and design the optimal energy production plan that hybridizes the existing centralized power grid infrastructure with the new distributed generation infrastructure. In this thesis, our approach was to 1) Utilize geospatial datasets and multi-criteria decision analysis to determine the optimal geospatially suitable sites for specific renewable DG developments (section 3) and 2) Quantify and compare the net values of conventional coal energy and various renewable energy alternative such as solar, wind, and hydropower in MWh units to determine the optimal usage ratio between conventional coal energy and DG energies (section 4). And finally, the thesis concludes with a summary of feasible locations to develop various distributed generation systems to advance the transition to reliable and sustainable energy production in West Virginia.

Section 2 Background & Literature Review

2.1 Energy Security in West Virginia

Energy security is defined by the International Energy Agency (IEA) as the uninterrupted availability of energy sources at an affordable cost. Today, energy security is a more complex issue as it focuses on different energy sources' economic feasibility, reliability, and environmental safety (Miller, 2011). There are various aspects to energy security, and the most common aspect refers to long-term security, which is the investments in energy that are made according to economic development and environmental needs. The United States has been a historically energy-secure nation but increasing worldwide movements away from high-emission energy resources have pressured the government to retire many conventional coal-fired power plants. As a result, the U.S. has scheduled to retire 23% of the entire coal-fired capacity by 2029 and has been reevaluating its energy policies and strategies to face upcoming changes in the country's energy infrastructure (EIA, 2022) (Bang, 2010). Changes stemming from these new regulations will likely impact energy security in several states heavily dependent on the traditional coal mining industries and their coal-fired power plants, particularly in West Virginia.

West Virginia has produced almost all the state's electricity through conventional coal-fired power plants, contributing about 91% of the entire generation in 2020(EIA, 2021). The conventional centralized energy grid in West Virginia has served as a major electricity distribution network for coal-fired power plants, connecting transformers, transmission lines, transmission substations, distribution lines, distribution substations, and eventually delivering to consumers (Rafique, 2022). They are usually large power grids located far from energy consumption areas; therefore, electric power is conveyed via long transmission lines and flows unidirectionally from the power grid to substations and then to consumer outlets. Most conventional power grids were built decades ago and are now outdated and require monitoring and frequent maintenance to provide stable electricity transmission. Higher electricity usage by modern-day society coupled with an obsolete power grid infrastructure increase the risks of power outages in energy-vulnerable regions. Moreover, nearly two-fifths of West Virginia's electricity is consumed by the state's industrial sector. Due to this heavy reliance on conventional energy grids and centralized coal power plant infrastructures, West Virginia is particularly vulnerable to power outages and their negative economic impacts (Figure 1; EIA, 2021). The significant contribution of the industrial sector to West Virginia's overall energy consumption, accounting for 47%, amplifies the potential damages associated with outage costs, thereby posing a critical impact on economic growth.

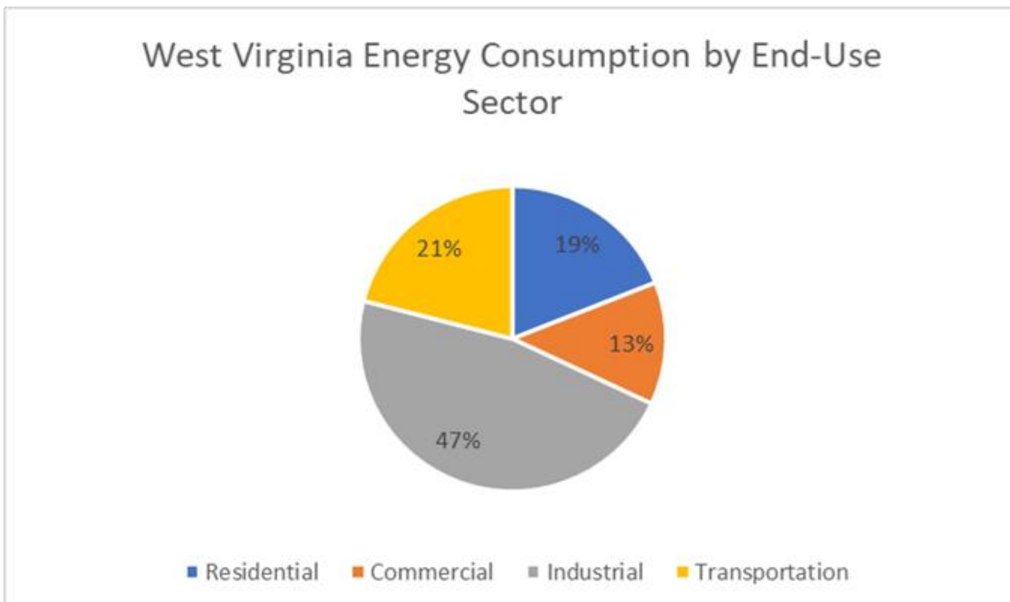


Figure 1-WV Energy Consumption by End Users

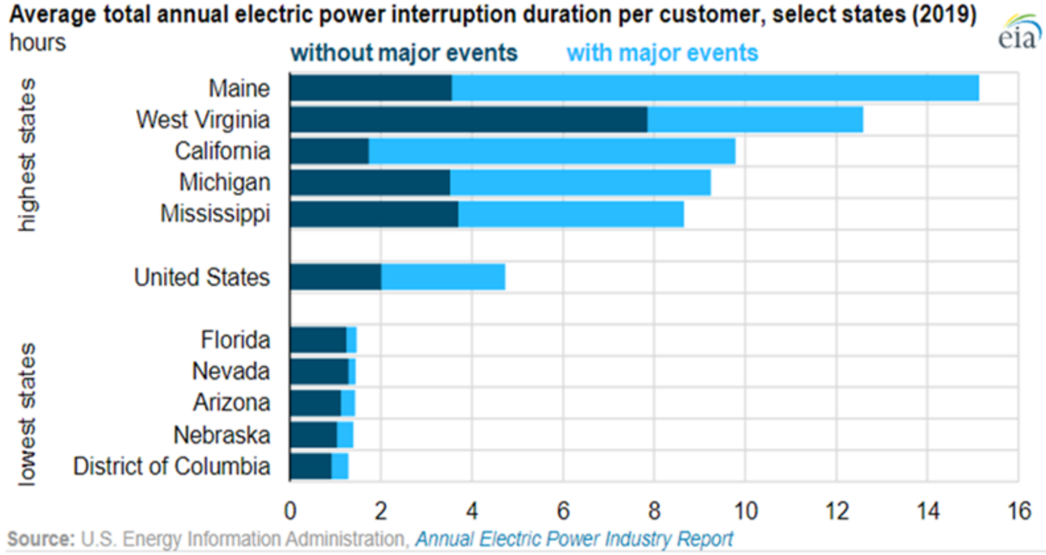


Figure 2-2019 US annual average power outages hours by states

Furthermore, West Virginia's rough mountainous terrain and dense forest cover are also factors that affect energy security and lead to potential power outages. Most existing conventional power lines in West Virginia must travel through miles of undeveloped, forested land to reach regional substations that connect to local households. Those power lines are susceptible to severe weather events such as flooding, storms, and heavy precipitation. According to figure 2, in 2019, the U.S Energy Information Administration (EIA) recorded that West Virginia has the highest average total annual electric power interruption per customer, with 8 hours without any significant environmental hazard events. West Virginia was also the second in interruption hours related to a significant hazard event, at 12.59 hours (EIA, 2020). Considering West Virginia is an energy state primarily through coal production and despite its recent decline in the coal industry, Figure 2 provides an interesting perspective on reliability of the state's energy and power infrastructure.

Previous energy resilience studies have mainly focused on the impacts of major events on outages while largely overlooking the local- scaled power interruptions from small power distribution lines failures. The Journal of Safety Science and Resilience recently published a study in 2022 that used Customer Average Interruption Duration Indexes (CAIDI), System Average Interruption Frequency

Indexes (SAIFI), and System Average Interruption Duration Index (SAIDI) to assess state-level energy resilience in the United States from 2002 to 2019 (Ankit et al., 2022). The EIA data collected for this study were conducted with regression analysis and concluded that West Virginia is among the states with the highest level of energy resilience during large-scale power outages. According to this study's regression analysis, West Virginia should experience the least amount of power outage occurrences (Ankit et al., 2022). However, the records from EIA in figure 2 demonstrated the opposite facts to most of the existing energy resilience reports: West Virginia is not energy-secured and has experienced increasing power outages in the past years. It is important to note that the existing literature on outages and energy resilience tends to focus only on large-scale statewide power outages or natural disaster-related power outages, and most power outage data does not include local and county-level outages and interruptions. Due to bias in these data, West Virginia's energy reliability may have been overestimated, resulting in less attention paid to maintaining and upgrading its outdated energy infrastructure that is causing more outages.

If West Virginia's current energy security policy and strategy remain unchanged, the state is likely to experience more power outages and interruptions due to increasingly extreme weather events caused by climate change in the coming years. These unstable electricity transmission and power grids can negatively impact the quality of life for residents, particularly those in remote rural areas where repairs and maintenance take longer to complete. The recurring outages also add financial pressure to residents, despite West Virginia having one of the lowest average electricity prices in the country. In fact, Appalachian Power and Wheeling Power reported a 7.4% increase in their customers' utility costs between 2020 and 2021 (WVPSC, 2021).

2.2 Distributed Generation

The traditional centralized power grid infrastructure has limitations in managing energy fluctuations due to its one-way distribution system, making it challenging to integrate alternative energy sources into the existing grids (Khoussi, 2017). In contrast, distributed generation (DG) systems have the potential to alleviate the net load stress placed on conventional power plants' centralized grids by utilizing diverse renewable energy sources. DG fundamentally utilize various renewable technologies to generate electricity to be consumed very close to the production vicinities, whether through solar panels, wind farms, or hydroelectricity (EPA, 2021). DG systems can be implemented in individual households, single industrial facilities, or local microgrids. Unlike centralized distribution, DG networks can incorporate all types of renewable energy into the grids due to their self-sustained and segregated characteristics (Viral & Khatod, 2012), providing a more flexible and resilient energy system.

The application of distributed generation systems is contingent upon the size of the community and its energy demand. This thesis focuses on planning the implementation of DG systems predominantly at the local community level. Site-specific renewable energy technologies, including solar panels, wind farms, and hydroelectricity systems, can be employed for different local DG projects (Viral & Khatod, 2012). As West Virginia's rural communities possess varying geographical conditions for specific renewable energy options, thorough spatial analysis is necessary to identify suitable locations for each DG system.

The reliability of small DG systems has previously been studied using probabilistic analysis. The analysis is conducted by a hybrid model combining an analytical method for assessing network reliability along with Monte Carlo simulation to predict the possibilities of all potential outcomes when the intervention of random variables is present (Borges & Cantarino, 2011). The results indicated that microgrids within a distributed generation network would improve reliability significantly; however, the stability indices are reduced when the generators are mainly powered by fluctuating energy such as wind or solar (Borges & Cantarino, 2011). The future implementation of an energy storage system with more consistent renewable energy input will significantly reduce the inconsistent generation and random behavior of DG, thus optimizing the performance, efficiency, and benefits of DG systems (Borges & Cantarino, 2011).

Investments in DG have the potential to benefit local communities, including the development of energy-efficient systems, advancements in DG technology, and improvements in electrical grid infrastructure (Parag & Ainspan, 2019). DG investments can stimulate the growth of other renewable energy technologies, leading to increased energy production and demand for goods and services. The economic benefits of DG can be divided into direct and indirect categories, with significant variation in the estimated value of the latter, especially in terms of economic incentives for rural communities (Parag & Ainspan, 2019). Given the ongoing advancements in technology, it is expected that the efficiency of DG will improve, and its costs will decrease, resulting in even greater long-term economic benefits than current estimates suggest.

2.3 LCOE/LACE

The levelized cost of electricity (LCOE), as determined by the EIA, represents the average revenue needed for each unit of electricity generated or discharged to recover the construction and operation costs for a generating unit (EIA, 2022). It can also be defined as a specified return on investment over a specific energy project based on the project's utilization rate. The EIA releases an annual report on LCOE estimations for energy generation technologies entering service in 2024, 2027, and 2040 since LCOE calculations are essentially predictions of costs and returns that change over time as technology advances or policies change. The equation for LCOE can be expressed in slightly different ways, depending on the supplementary methods provided by different agencies and organizations. The general equation provided by the EIA (2015) is:

$$LCOE = \frac{fixed\ charge\ factor * capital\ costs + fixed\ O\&M\ costs}{Expected\ Annual\ Generation\ Time(hours)} + variable\ O\&M\ +\ fuel \qquad (1)$$

The levelized cost of electricity (LCOE) calculation uses the capital cost as the initial investment per generation unit capacity in a project and varies for each energy source’s technologies, such as solar, wind, and hydropower. Capital costs are subject to change over time due to adjustments to new technologies or economic factors and are expressed in $/Megawatt (MW). The fixed charge factor annualizes the capital costs based on the weighted average cost of capital, federal tax burden, and the project's financial lifetime. Fixed O&M represents the annual operations and maintenance costs per generation unit within the project capacity and is expressed in $/MW/year. Expected Annual Generation Time (hours) represents the number of hours for one generation unit in a year that is expected to operate. Variable O&M accounts for the cost of specific items and equipment and is measured by the actual hours of operations. Fuel represents the cost of fuel and is expressed as the hourly average of the long-term fuel costs over the equipment's assumed financial life. Finally, all LCOE calculations cancel out the year and are expressed as dollars per megawatt-hour ($/MWh).

In contrast to LCOE that estimates the revenue required to build and operate a generator, levelized avoided costs of electricity(LACE) estimate the revenue available to the generator from the sale of energy generation and production(EIA, 2015). The equation for LACE is presented as

$$LACE = \frac{(Marginal\ Generation\ Price * Dispacthed\ hours)+(cap\ payment*cap\ credit)}{Expected\ Annual\ Generation\ Time(hours)} \tag{2}$$

The marginal generation price represents the cost of providing energy to match demand during a specific time period, which can be influenced by environmental policy requirements. Dispatched hours refer to the estimated number of hours that a generation unit is dispatched. Cap payment is the capacity payment value necessary to utilize an energy asset's capacity. Capacity credit is a percentage-based system used to quantify a generation unit's ability to provide energy reliability reserves, corresponding to the availability of renewable resources, such as the weather's impact on wind and solar energy. Expected annual generation hours are identical to those used in LCOE, representing the annual operating time for a unit (EIA, 2015).

These two equations and their results are critical for the development of DG in West Virginia, as they provide statistical assessments of specific energy types' economic incentives for investment and development. The Net Value, calculated as the difference between LACE and LCOE, indicates potential profit or loss and suggests economic incentives for specific distributed energy types (EIA, 2015).

$$Net\ Value = LACE - LCOE \tag{3}$$

For the DG suitability analysis, the LCOE and LACE were compared between the available renewable energy sources in West Virginia to determine the economic feasibility for the DG development.

2.4 Social Cost of Carbon

The Social Cost of Carbon (SCC) is a measure used to estimate the incremental damages and impact of carbon emissions, serving as an important method for monetizing the external costs cost of carbon emissions as well as assessing potential energy regulations. SCCs are crucial for the economic analysis and implementation of climate policies (Wang et al., 2019). While SCC estimation theoretically indicates carbon pricing, the values of carbon prices change depending on the specific environmental policies and regulations in place.

In the analysis of DG net value comparisons, I intended to incorporate SCC into the LCOE calculations for the conventional centralized coal energy in West Virginia and compared with wind, solar, and hydropower DG systems. The inclusion of SCC would increase the economic incentives for developing DG systems as it increases the cost of conventional coal-fired power plants. Distributed energies benefit from avoiding SCC, thus enhancing their value and attraction for investment. The avoided SCC can then be calculated as a potential profit for DG systems in addition to their LACE values.

The Integrated Assessment Model (IAM) is a key method for estimating SCC over time, as it allows for adjustments to changes in factors such as technology costs and environmental conditions. The application of different damage functions to IAM, depending on the climatic sensitivity of different regions, results in various equations and parameters being used to estimate the SCC based on specific regions or policies. However, this makes it difficult to determine an accurate cost of carbon. To address this issue, Wang et al. (2019) conducted a meta-analysis of 578 SCC estimates from 58 studies, with results ranging from -13.36 to 2386.91 \$/t CO_2 and a mean value of 200.57 \$/tC (54.70 \$/t CO_2). Notably, this mean value is very close to the official SCC values released by the U.S. White House in 2021, which estimated SCC values from 2020 to 2050 with 2.5%, 3%, and 5% discount rates (Table 1; White House, 2021).

Table 1-Social Cost of CO2, 2020 – 2050 (in 2020 dollars per metric ton of CO2)

Emission Years	5% average discount rate	3% average discount rate	2.5 % average discount rate
2020	14	51	76
2025	17	56	83
2030	19	62	89
2035	22	67	96
2040	25	73	103
2045	28	79	110
2050	32	85	116

The SCC estimate from the U.S. Whitehouse at a 3% discount rate is widely used as a benchmark for carbon emission analysis in the United States (White House, 2021). However, state environmental conditions and regulations can affect the discount rate percentage. For example, New York and Washington State issued their own SCC estimations with lower discount rates to implement cleaner energy plans. Our analysis will use a 3% discount rate based on 2025 dollar values for West Virginia's SCC, valued at \$56/mton of CO_2, and consistent with Wang et al (2017)'s SCC meta-analysis mean value of \$54.7/mton. This SCC estimate will be the avoided costs for our DG systems and added costs for conventional coal energy in West Virginia.

2.5 Multi-Criteria Decision Analysis

Multi-criteria decision-making (MCDA) simplifies complex problems by ranking potential solutions based on multiple criteria to determine the best option (Jiang & Eastman,2000). MCDA is commonly used in energy planning to identify suitable sites based on predefined criteria. In GIS-related studies, MCDA helps pinpoint appropriate locations for renewable energy sources such as solar and wind farms (Wang et al., 2009). The Analytical Hierarchy Process (AHP) is a popular MCDA method that uses pairwise comparisons to determine criteria weights (Saaty,1988). These weights are then aggregated onto a map to highlight optimal locations for specific research purposes.

Al Garni & Awasthi (2017) utilized MCDA that integrates the AHP method to perform a solar site suitability analysis. They selected geospatial variables and assigned weights to seven criteria containing physical and economic factors such as solar irradiation strength, temperatures, and proximity to urban areas. Then, they applied weight sum overlay in ArcGIS to combine all the weights and create an integrated analysis, displaying the final suitable sites for solar farms in Saudi Arabia. A recent study by Ajanaku et al. (2022) applied the AHP method to wind farm site selection in West Virginia. The authors used pairwise comparison of ten criteria to determine the weights for each criterion and combined them with constraint layers that excluded areas unsuitable for wind farm development. They also incorporated past experts' weights for the criteria and assessed model consistency using the consistency index provided by Saaty (1988). Ajanaku et al. (2022) produced a map layer highlighting the optimal wind farm construction sites in West Virginia. Similarly, Ahmed et al. (2021) used the MCDA model combined with the weighted linear combination in GIS to perform a hydroelectric storage plant suitability analysis in Egypt. They reclassified suitable criteria and assigned weights to them, computed the weighted average for each nearby raster cell, and produced a site suitability analysis.

Previous energy planning studies have utilized MCDA and AHP methods to select criteria for their specific research purposes. Our study employs a similar AHP process of assigning weights to site suitability criteria for solar, wind, and hydropower energy and identifying feasible sites for each energy. However, our approach differs from prior studies as our MCDA process focuses on identifying suitable sites for small, distributed energy in rural communities, rather than large-scale energy infrastructure.

Section 3. DG Spatial suitability Analysis & Dataset

3.1 Study Area

This study focuses on analyzing the suitability of distributed energy for rural communities and regions in West Virginia with low population density and energy resilience, as measured by higher rates of power outages. To ensure the accuracy of the study's findings, population hotspots such as Charleston, Morgantown, and other urbanized areas will be excluded from the spatial and site suitability analysis. Although the existing political boundaries, such as county borders, do not always accurately reflect population density, rural areas can be defined as open countryside with fewer than 500 people per square mile and fewer than 2,500 residents, while urbanized areas and urban clusters are defined by the Census Bureau as places with urban nuclei of 50,000 or more people and areas with a population of at least 2,500 but less than 50,000(Census Bureau 2020). USDA also recognizes that the population distribution line that divides urban and rural does not follow municipal boundaries, and most counties possibly contain both urban and rural populations (USDA, 2020). This study's suitability analysis will depend heavily on reclassifying the population density and creating population clusters as an essential factor in determining potential DG sites.

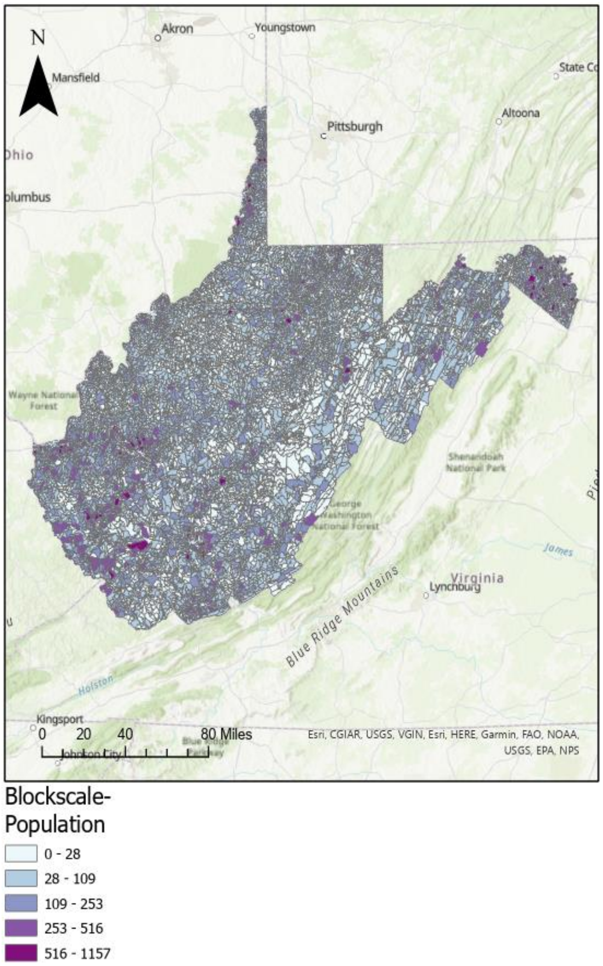
The potential study areas are also influenced by West Virginia's land use and land cover. The suitability of land covers for DG development varies depending on the type of DG system used. Effective DG systems should be located in open spaces with minimal vegetation and away from highly developed areas (Wolsink, 2018). Forests and developed areas can increase investment cost and pose environmental challenges, making them less preferred options (Wolsink, 2018). While wetlands and open water bodies are generally unsuitable for wind and solar distributed generation (DG), hydroelectricity DG may actually require water bodies for its operation. Therefore, the evaluation criteria for hydroelectricity DG suitability differs from wind and solar DG.

3.2 Census Bureau Population dataset

County and municipal borders are inadequate in reflecting the distribution of population and its statistics. As a result, smaller-scale census data, such as census tracts and census blocks, are preferable for a more precise representation of population distribution within county boundaries. Census tract and block boundaries provide a more detailed population distribution than county boundaries, as they can change with local population changes (Census Bureau, 2020). Tracts typically have a population of 1,200 to 8,000, while blocks are the smallest geographic units used by the Census Bureau, enabling a more in-depth population density analysis.

Census population data is limited in analyzing population distribution due to imprecise statistical boundaries at the county or census tract level. The real-life population distribution does not follow geopolitical boundaries and is too spatially spread out. Figure 3 shows the precision differences between census block, tract, and county scale population datasets through ArcGIS hotspot analysis. We use weighted features to identify significant hot and cold spots in West Virginia, which indicate clusters of high and low population values.

To ensure maximum accuracy, we will utilize the census block population dataset to calculate population density and generate population clusters. This dataset provides better visual presentation and accuracy compared to larger census units. The population density map in figure 3-d was created using the census block data and provides a clear visualization of one-mile squared population clusters, ranging from around ten people per square mile to over two thousand people per square mile. In accordance with the USDA's definition of rural, suitable clusters will have a population density of less than five hundred people per square mile (USDA, 2020).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Akron
Youngstown
Mansfield
Pittsburgh
Altoona
Ohio
Wayne National Forest
Shenandoah National Park
George Washington National Forest
Blue Ridge Mountains
Lynchburg
Virginia
James
Holston
Kingsport
0 20 40 80 Miles
Esri, CGIAR, USGS, VGIN, Esri, HERE, Garmin, FAO, NOAA, USGS, EPA, NPS
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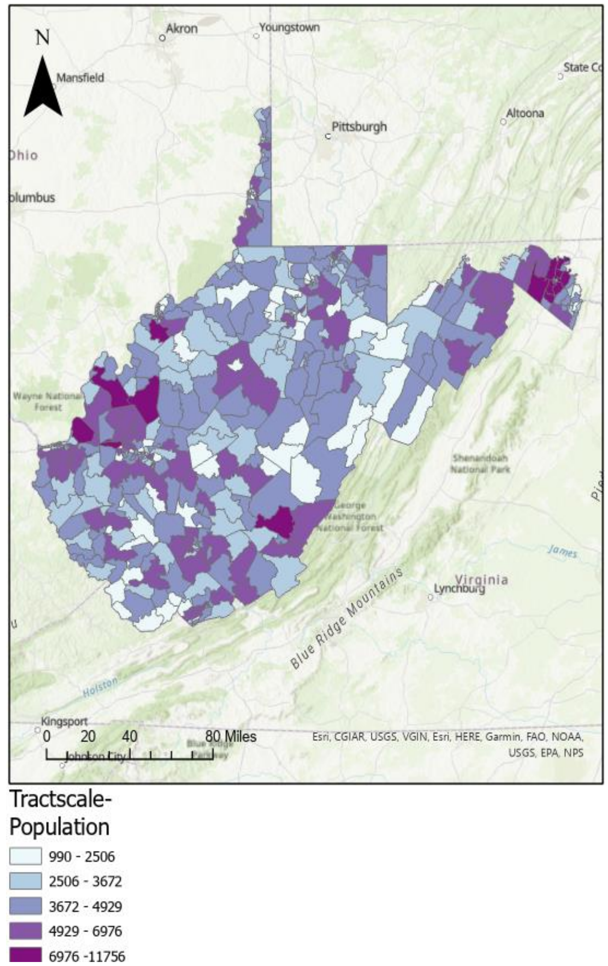
516 - 1157

a.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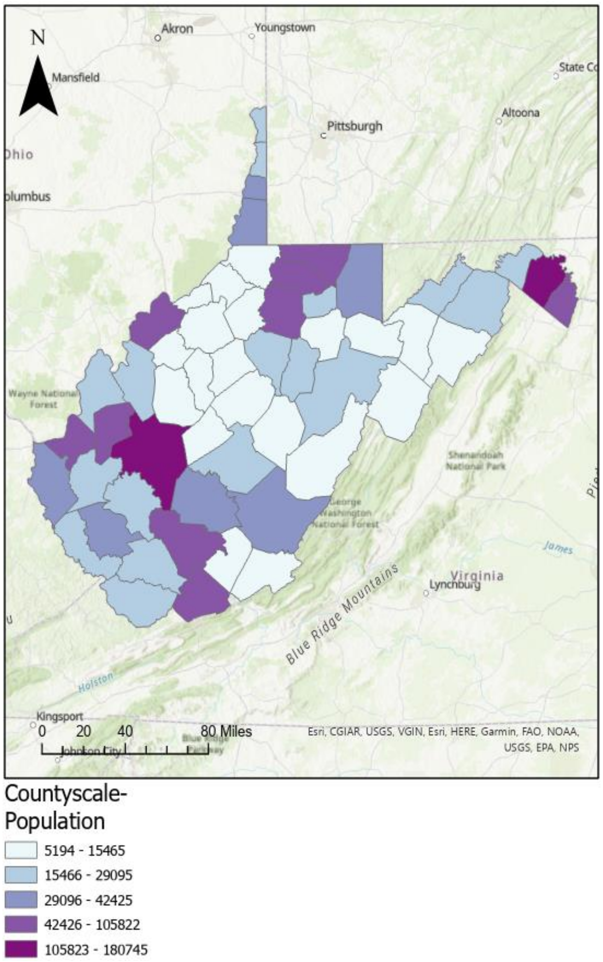
b.



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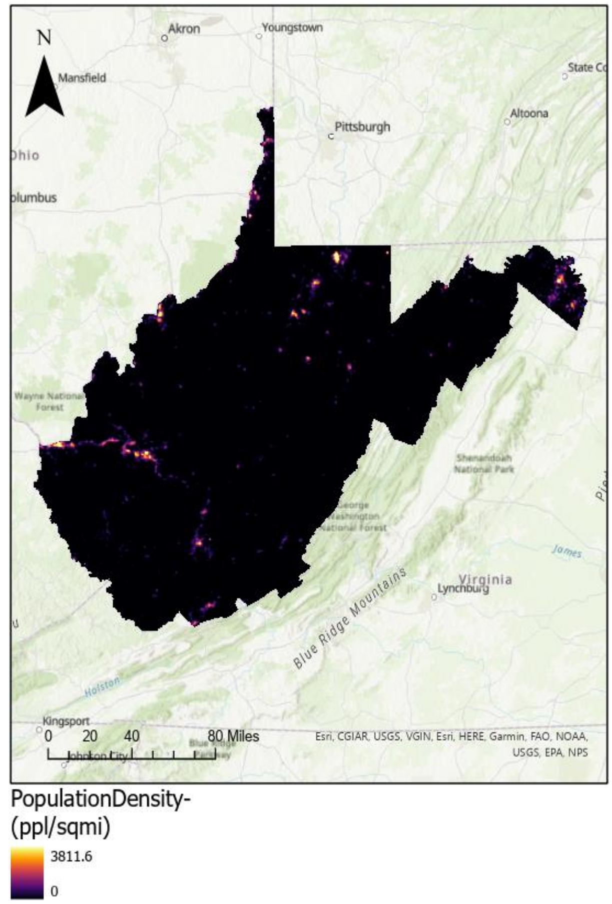

d.

Figure 3-Census Bureau population maps: a) census block scale population, b) census tract scale population, c) census county scale population, d) population density per square mile based on census block.

3.3 National Renewable Energy Laboratory (NREL) Datasets

3.31 NREL Solar Dataset

There are two types of solar resource datasets provided by NREL: Global Horizontal Irradiance (GHI) and Direct Normal Irradiance (DNI). Typically, DNI has been used for Concentrated Solar Power (CSP) or Concentrated Solar Thermal (CST) plants since these plants generate electricity using the direct normal irradiance (DNI) component of solar irradiance (Law et al., 2014). In most CSP solar systems, mirrored surfaces are used to focus solar irradiance onto a receiver with a heat transfer device, which rotates along with the solar source. In most cases, the heat generated by the receiver can be used to mechanically spin the turbine and power an engine to generate electricity (Dawson & Schlyter, 2012). In order to be considered commercially viable, CSP systems have a relatively strict installation requirement, including the requirement for a high DNI location with a preferred threshold of 2000+ kWh/m2/year, or about 5.5 kWh/m2/day (Breyer & Knies, 2009). Additionally, the terrain requirement is critical for CSP infrastructures since CSP technologies are limited in terms of how they design the solar field to capture DNI. The feasible ground slope to install CSP should be at least 2.1%, and anything beyond 2.1% is deemed unsuitable for large-scale CSP or requires a significant increase in investment (Trieb, 2009). As a result of such strict installation conditions, land availability is significantly reduced, especially for CSP, which requires a large amount of land. Therefore, there is the possibility that opportunity costs will increase when CSP needs lands where another intensive land use exists, such as agricultural land, residential areas, and highly productive industrial areas (Dawson & Schlyter, 2012).

DNI measurements of solar resources are also sensitive to weather conditions and require direct radiation capture with less diffused irradiation from clear sky conditions. West Virginia's mountainous and forest terrain and rainy weather already hinder the possible suitable sites for many sizeable solar power systems distributed generations. Therefore, DNI dataset from NREL is not a preferable option to be used for small-scale DG's site suitability analysis. As opposed to DNI, GHI measures the total solar radiation incident on a horizontal surface, which is the sum of directed normal irradiance (DNI), diffuse horizontal irradiance, and ground-reflected irradiance. GHI is a more realistic solar dataset that is suitable to West Virginia's physical terrain, land availability, and weather conditions, which makes this dataset more applicable to communities that are only suitable for smaller solar panels and smaller scaled distributed generated solar systems.

NREL's GHI datasets were collected by the Physical Solar Model (PSM) version 3. By employing a physics-based model to deliver gridded solar radiation data for the whole United States utilizing geostationary satellites at 4 km x 4 km resolutions, the PSM 3 is essentially an update for the conventional empirical modeling of solar radiation data collecting from individual stations (NREL, 2020). The unit of the GHI dataset is kWh/m2/day, with the highest of 4.34kwh/m2/day and the lowest of 3.91Kwh/m2/day in West Virginia (figure 3), which is about average to low tier GHI level in the entire U.S according to the national solar radiation database.

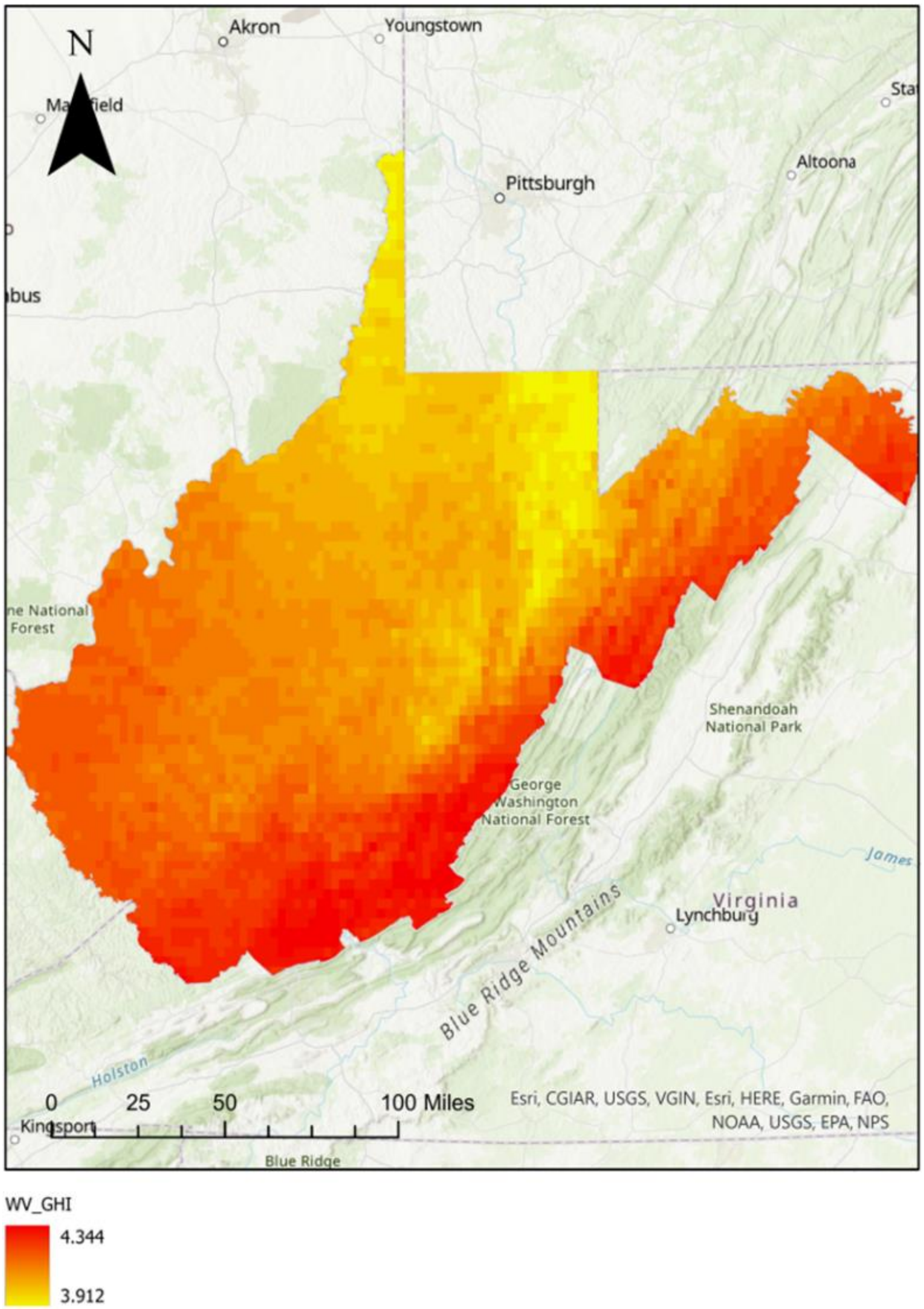

Figure 4-WV Global Horizontal Solar Irradiance (kWh/m2/day)

3.32 NREL Wind Dataset

To exploit better wind resources higher in the atmosphere, utility-scale, land-based wind turbines are typically built between 80 and 100 m high, while tower heights for new installations are rising up to 140 m. Our study used the 80 meters above surface wind speed dataset since 80 meters is commonly regarded as a reliable and suitable source of wind power development (Latinopoulos & Kechagia, 2015). More extensive and higher wind turbines theoretically have the capacity to produce better energy production. However, they will also require increased investment and potentially be less economically viable for our targeted rural communities. The NREL's annual technology baseline provides constantly updated references for renewable energy resources. The land-based wind resource classes are a relatively new classification that simplifies the wind resources data based on only annual max wind speed(m/s), minimum wind speed(m/s), and annual mean wind speed (Table 3) (NREL, 2020).

Table 2-NREL Land-Based Wind Resource Classes

Wind Speed Class	**Min. Wind Speed (m/s)**	**Mean. Wind Speed (m/s)**	**Max. Wind Speed (m/s)**
1	9.01	10.95	12.89
2	8.77	8.89	9.01
3	8.57	8.67	8.77
4	8.35	8.46	8.57
5	8.07	8.21	8.35
6	7.62	7.84	8.07
7	7.1	7.36	7.62
8	6.53	6.81	7.1
9	5.9	6.21	6.53
10	1.72	3.81	5.9

The range of the wind speeds is categorized into ten wind speed classes from 1.72m/s to 12.89m/s. Wind speed class 4 (8.35-8.57m/s) is considered the average wind speed in the United States that is feasible for wind resource projects, which also represents a majority of US wind resource project standards indicating sufficient and moderate quality wind resources (Maclaurin et al., 2019). However, NREL's wind speed class 4 is not a set rule for all wind farms and wind resources projects. Latinopoulos & Kechagia (2015) and Ajanaku et al. (2022) have produced wind farm suitability analyses for 80-meter wind turbines with a yearly average wind speed of about 6.5 m/s and above. West Virginia's 80-meter annual mean wind speeds ranged from 3.57 to 11.44 m/s, which is exceptionally applicable for potential wind energy DG systems at selected sites. There are also existing wind turbines already installed in several counties, and we can use them as future references to see if our suitable wind sites accurately reflect wind resource potentials.

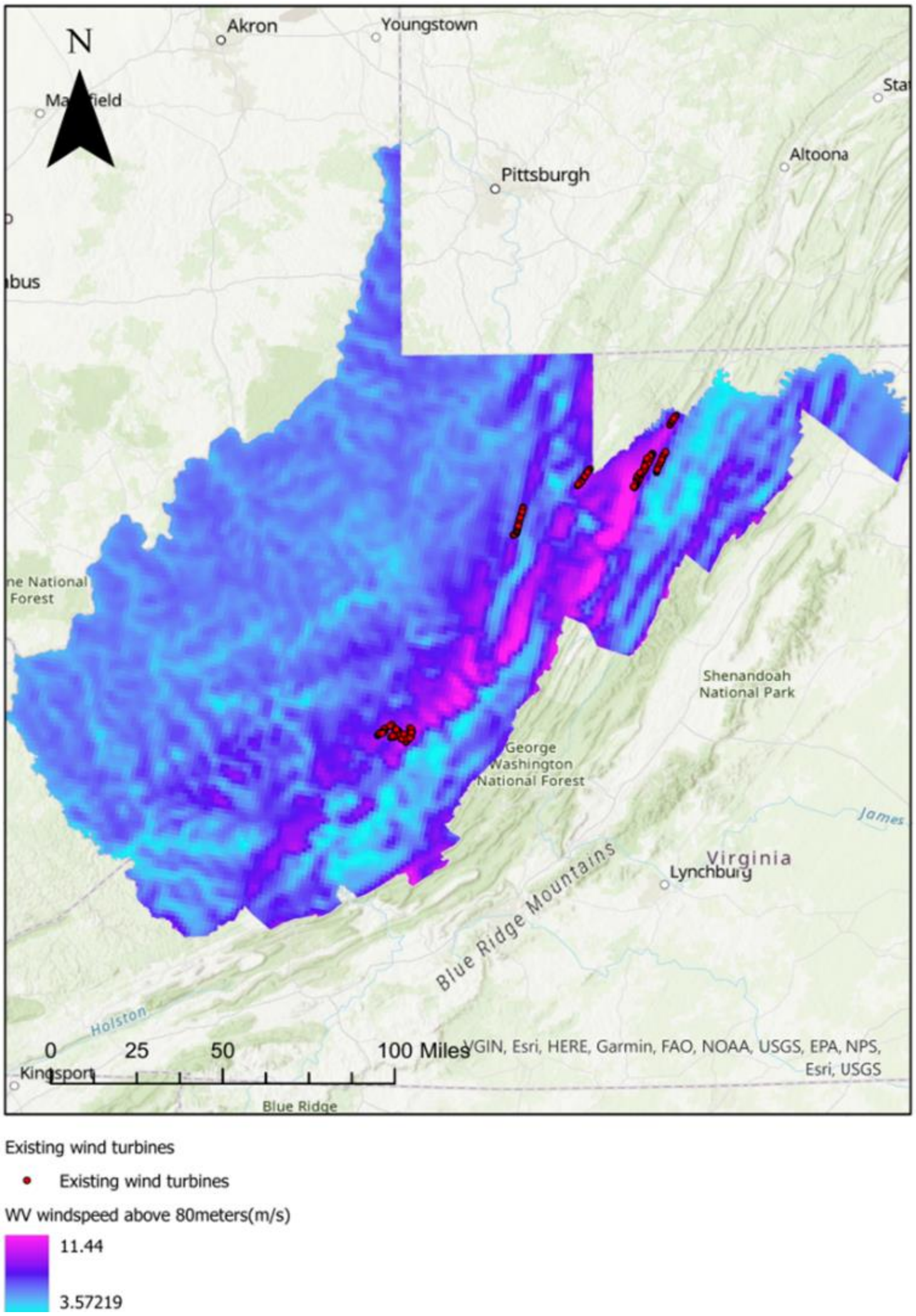

Figure 5-WV Annual average wind speed at 80 meters above the surface level

3.33 NREL Small Hydroelectricity Datasets

The Small Hydroelectricity Dataset (SHD) from NREL is based on the report and survey from previous studies from the US Department of Energy (DOE). Water energy resources and hydroelectricity development have been an ongoing interest for the DOE. Therefore, DOE and U.S. Geological Survey conducted water energy resource assessments of all 20 hydrologic regions in the past years to identify and measure undeveloped hydropower resources, specifically for low power and small hydro project without total stream impoundment (Department of Energy, 2013). This report utilized the digital elevation models and GIS tools to compute the waterpower potential of every natural stream segment in the US and compared the states and regional water energy potentials to determine regions with abundant and concentrated water energy resources that are underdeveloped.

The small hydro feasibility analysis was first performed in 20 hydrological regions and then combined to produce the nationwide state-by-state results. The main criteria to determine the small hydropower feasibility included the annual mean flow rate of the associated streams, gross hydraulic head, proximity to existing power infrastructure, and distance to populated areas (Hall, 2006). The results from this assessment indicated that West Virginia's existing hydro energy development has about 140 MW hydro energy but has 484 MW of potential hydropower remaining undeveloped, which means potential growth of 346% in small hydropower resources (Department of Energy, 2013). This report provided GIS datasets for Feasible Small Project Sites (FSPS) that represent small hydropower of less than 30MW. We extracted the output GIS datasets to West Virginia for our analysis (Figure 6) and utilized these small hydro sites as references to identify feasible sites for our small hydro DG analysis. We then added further criteria specific to small hydropower DG development to locate suitable sites.

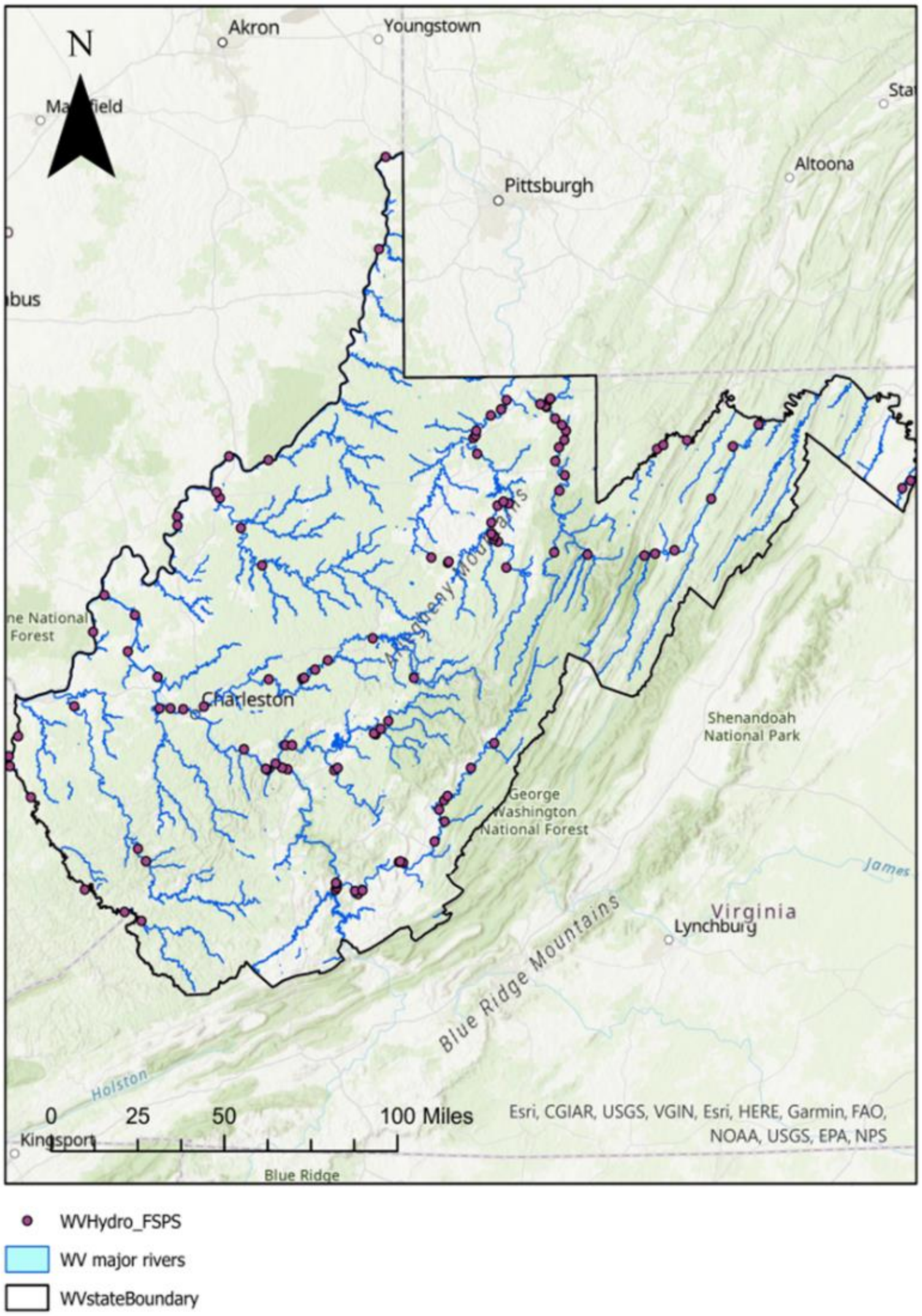

Figure 6-WV Feasible Small Project Sites for Hydroelectricity

3.4 Power Outage Dataset

Power outage is a unique criteria factor in our DG site suitability analysis and provides an interesting outlook for West Virgin's energy resilience issues. We intended to use the power outage dataset to prioritize DG infrastructure development in rural regions that experience more power outages. The datasets obtained for our analysis were purchased from PoweroutagesUS, which contains all West Virginia counties' 12 months' outage records in the past five years, from 2017 to 2022. This dataset also includes major power suppliers, the average population tracked with each utility company, monthly numbers of customers who experienced outrages, the total outage hours, and total hours of services tracked to all customers in each county.

This dataset's total hours of outages are the sum of all customers' outrages hours. This causes counties with higher populations to have higher records of outage hours. Therefore, we aimed to eliminate this bias in the data by only utilizing the averaged tracked populations that experienced outages in counties in the past five years. The recorded population affected by monthly outages per county allowed us to compute the ratio with existing county populations to determine the percentages of people who experienced monthly outages in the past five years (Figure 7).

We displayed the outage data in ArcGIS (Figure 7). The output indicated that Webster County has the highest monthly percentage of people experiencing outages (48%), followed by Pocahontas County (31.6%), Clay County (35.9%), Lincoln County (38%), Wayne County (34.5%), and Wirt County (32.5%). These counties with a higher percentage of their population experiencing outages were our priorities for developing community-scaled DG infrastructures, but we also did not exclude other regions and counties for the site suitability analysis.

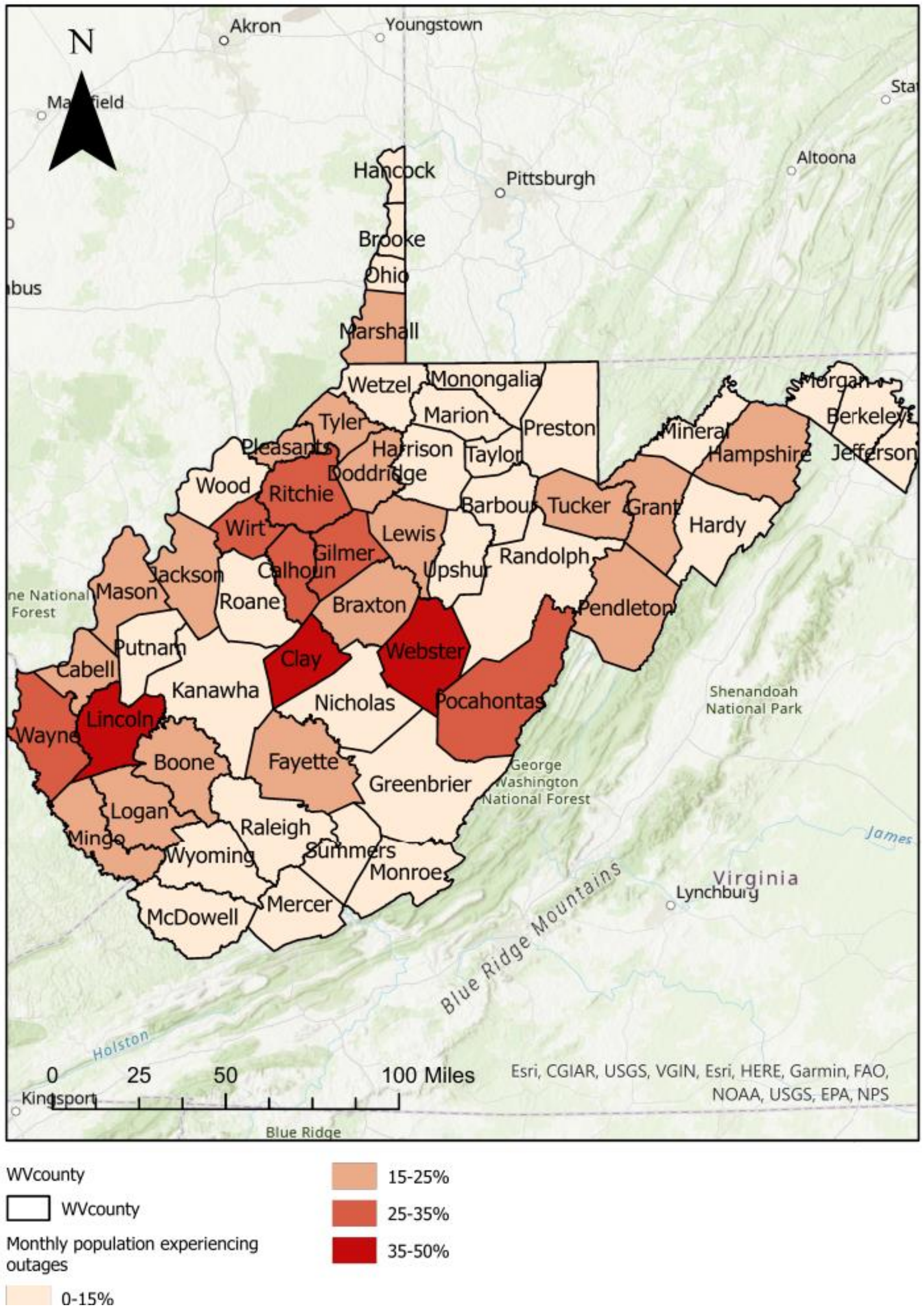

Figure 7- WV Monthly outages' affected population percentage

3.5 Methods

Multi-Criteria Decision Analysis (MCDA) was used in our study for all three types of DG systems. The physical attributes and requirements for distributed generation vary depending on the renewable technologies. Solar, wind, and hydro have similar yet different requirements and criteria for site suitability assessments. We first created constraint layers in ArcGIS Pro™ for each DG resource based on specific suitability requirements. In our spatial analysis, all GIS functions and layers that were produced were projected into NAD 1983 UTM Zone 17. All output raster datasets were generated to 30-meter resolution. Euclidean distance tool from ArcGIS™ spatial analysis was utilized to create distance from power substations, protected areas (National Wildlife Refuges areas, West Virginia Wildlife Management areas, and National/Historical parks), populated residential areas, and other criteria applied to each individual distributed energy. Next, we determined the optimal range of these criteria based on previous research from our literature reviews, such as the distance away from power grids, most optimal wind speed, solar radiation, and hydropower.

The AHP pairwise comparison matrix was executed to determine the weight for each criterion before combining all constraint layers to increase analytical accuracy. For this study, we used the simplified pairwise measurement to reduce cognitive burden as opposed to the conventional pairwise method from the 9-point scale to the 4-point scale, as Strager & Rosenberger (2006) noted in their analysis (Table-3). We calculate the pairwise comparison matrix based on past expert reviews and weights for different criteria. After the pairwise comparison process, consistency tests were required because the criteria in the pairwise comparison could be illogical and random. The most popular consistency tests were presented by Saaty (Saaty, 1988), and the consistency index (CI) is given by

$$CI = (\lambda - n)/n - 1 \qquad (4)$$

Where λ measures the maximum eigenvalue, and n represents the numbers of criteria. Then we utilized the random index (RI) proposed by Saaty to calculate the consistent ratio (CR).

$$CR = CI/RI \qquad (5)$$

According to Saaty, CR values below 0.10 are indicative of acceptable consistency for pairwise comparison matrixes (Saaty, 1988). It should be noted that certain criteria used in our study were unique to the smaller-scale community-based distributed generation systems, such as power outage percentages and population density. These criteria had no prior expert weights references, thus the pairwise comparison weight results were subjective to our analysis. We employed the weighted sum function in ArcGIS Pro to integrate the various criteria and weights specific to each DG system. The results were then reclassified to generate suitability output maps for each DG. Finally, we conducted a sensitivity analysis of all our GIS spatial results to test the stability of the weights obtained from the AHP pairwise comparison process.

Table 3-Simplified pairwise comparison alternatives

Traditional pairwise comparison rankings	Alternative/ simplified pairwise comparison rankings
Equal–1	Equal–1
Barely prefer–2	
Weakly prefer–3	Somewhat prefer–3
Moderately prefer–4	
Definitely prefer–5	
Strongly prefer–6	prefer–5
Very strongly prefer–7	
Critically prefer–8	
Absolutely prefer–9	Strongly prefer–7

3.51 Solar DG Evaluation Criteria and Constraints

Site suitability and assessment of solar energy resources for large solar PV farms are influenced by technical, economic, and environmental factors (Charabi & Gastli, 2011). However, these factors vary depending on the country, location, and environment. For instance, Oman, located in the arid and hot Middle East region, requires a higher solar PV value and considers site-specific constraints such as dusk and sand risks (Charabi & Gastli, 2011). On the other hand, England, which has a more temperate climate, focuses on solar radiation and distance from historically important areas to determine the suitability of solar farms (Watson & Hudson, 2015). In addition to solar irradiation values, the universal constraint criteria for solar energy infrastructure include slope degrees, distance to existing energy grids, and land use. To be economically feasible, solar farms should ideally be located on flat or mild slopes with less than 5% degrees. Furthermore, priority should be given to land uses with minimal value due to past usage and current conditions, as these factors can help reduce installation and construction costs (Watson & Hudson, 2015). Finally, the distance from electric networks and populated areas is often considered a favorable factor when setting up a distributed generation network and installing PV solar panels connected to the grid (Al Garni & Awasthi, 2017).

Evaluation criteria selection should be based on study goals, spatial scale, and the accessibilities of available datasets. As part of the solar DG suitability analysis for West Virginia, we have already reduced the potential DG development areas to rural communities that experienced higher rates of energy disruption. In our analysis, we focus criteria on population density that is less than 500 people per square mile to avoid urban population. Other criteria include Global Horizontal Irradiance values for solar strength, distance to electric substations, land use, and average percentages of people experiencing power outages over the last five years in all counties in West Virginia (Table 4).

After determining the constraints for our solar DG analysis, fuzzy logic membership in ArcGIS pro were employed to define each criterion's class membership. The Fuzzy logic membership function essentially smooths out the edges between simple yes and no (1 or 0) questions by adding the "human thinking" fuzziness (Charabi & Gastli, 2011). With fuzzy set membership, standardization differs from linear scaling because it emphasizes the relationship between the criterion and decision set. By inferring from indefinite, vague, or ambiguous information, fuzzy membership opens up broader options for set membership functions than linear rescaling (Jiang & Eastman, 2000). Then we applied the pairwise comparison matrix to give weights to each criterion. Al Garni & Awasthi (2017) listed multiple pieces of literature that applied MCDA methods to choose potential solar energy sites with weights that were assigned to different criteria. Our DG suitability criteria, such as solar power strength, slope, and distance to grids, were all in an acceptable range of differences.

Table 4-Solar DG Evaluation Criteria and Constraints

Criteria	Constraints	Description/Source	Weight
Population density (1-mile radius clusters)	<500 people	For small-scale distributed solar energy systems across West Virginia, we focus on rural communities that are not within urban clusters. USDA and the US census bureau define rural clusters as regions of fewer than 500 people per square mile (USDA,2020)	0.192
Solar Global Horizontal Irradiance	>4.3kwh/m2/day	As the most critical values for any solar energy projects; GHI requirement for solar farm or solar panels varies across the global (Charabi & Gastli, 2011). Solar GHI does not have a vast difference. In West Virginia, the highest average annual GHI is 4.34, and the lowest is 3.9 (NREL,2020). We applied the highest percentile of the solar GHI to achieve maximum solar efficiency for DG development.	0.406
Slope	<5%	Construction costs will be lower in flat or mildly steep areas than on steep slopes. Sites with less than a 5 % slope are preferred since flatter areas have higher economic feasibility to develop solar energy projects (Al Garni & Awasthi,2017)	0.105
Landcover/Land use	Reclassify the Landcover layer with Barrne as the most suitable sites, followed by other land covers on a 0 - 5 scale with five being most suitable, and zero as unsuitable.	Land use requirement is critical for suitable sites for solar energy, and barren lands are the most preferred option (Uyan, 2013). Prioritize barren, shrubs, hay/pasture, and some croplands. Open waters, developed lands, wetlands, and all forest land cover are deemed unsuitable for solar DG development.	0.101
Distance to substations	<6000 meters	Sánchez-Lozano. et al. (2014) conducted a collection of past experts' evaluations for distance to substations, which ranges from 4200 meters to 6400 meters, with most experts' evaluations around 6000 meters.	0.155
Power Outage percentage	>25%	Outage percentage criteria is unique to our analysis since it is based on the population in each county that has experienced power outages in the past five years. This criterion helps us determine the high-energy-vulnerable regions that can be prioritized for new DG development.	0.041

3.52 Wind DG Evaluation Criteria and Constraints

In this study, we found that the site suitability criteria for small-scale, community-size wind DG systems shared similarities with those for solar energy systems, such as considering population density and proximity to energy substations. However, wind DG infrastructure is more site-sensitive than solar due to its potential impact on the local environment and wildlife. As a result, it is challenging to determine constraint factors for wind energy projects because specific evaluation criteria are required based on the targeted locations. In the UK, Baban & Parry (2001) identified 14 constraint criteria associated with the environment and natural resources for wind site suitability analysis, including factors such as distance from historical sites and woodlands/forests. These previous studies' wind farm suitability criteria are site-specific to their regions and are not entirely applicable to our research in West Virginia due to differences in terrain and environmental conditions.

For example, West Virginia has rough mountain terrain and over 80% forest land cover (USGS, 2019), making it challenging to develop wind DG energy infrastructure without impacting forest or woodland land cover. However, Ready (2017) reported that the U.S. Forest Service approved the construction of a wind energy facility in Vermont's Green Mountain National Forest, demonstrating that wind energy projects can be built in national forests. Therefore, we are not excluding forest land cover from our potential wind DG development's suitability analysis (Table 5). In addition to our suitability criteria for small-scale wind DG for rural communities, we include protected areas to avoid significant environmental impacts through potential visual, noise, electromagnetic interference, and wildlife collisions that could cause additional environmental and wildlife damage (Baban & Parry, 2001).

Table 5-Wind DG Evaluation Criteria and Constraints

Criteria	Constraints	Description/Source	Weight
WindSpeed (80 meters above surface)	>6.5 meters/second	Despite the advancing wind turbine technologies that now support higher turbines at 120 meters and 150 meters. Smaller	0.282

		turbines at standard 80 meters are more suitable for our wind DG system. Baban & Parry (2001) listed the mean annual wind speed above 5m/s as the threshold for wind energy. We referenced a more recent wind farm study in West Virginia indicating the 6.5m/s threshold (Ajanaku et al., 2022).	
Slope	<10%	Mild slope is important for reducing construction and development costs. Among the range of expert constraint choices, many past experts utilized a 10 % slope as the constraint for wind farms (Ajanaku et al.,2022 ; Al-Yahyai et al.,2012). We believe the heavily utilized 10% slope constraints also suit West Virginia’s terrain for our analysis.	0.119
Distance to Substation	<6000 meters	Atici et al. (2015) presented a list of expert ratings for distance to national grids, ranging from 10000 meters to 250 meters. The distance to substations is more local grid infrastructure than the transmission line, and therefore, we chose a distance of around 6000 meters for our analysis that pairs with solar energy projects.	0.173
Distance to Airport	>3000 meters	The safe distance from wind turbines varies depending on the airport's size and air traffic, which ranges from 2500 to 5000 meters (Atici et al., 2015). The 3000 meters threshold is reasonable for West Virginia airports.	0.081
Distance to Protected Area	>2000 meters	Protected areas include the National Wildlife Refuges areas, West Virginia Wildlife Management areas, and National/Historical parks. Due to the importance of the National Park and wildlife conservation in West Virginia, we utilize the 2000 meters constraint, which is the highest constraint among the expert ratings (Atici et al., 2015).	0.072
Distance to river/streams	>1500 meters	Rivers and streams are not suited for any constructions for Wind DG due to the increased cost and environmental concerns (Al-Yahyai et al.,2012). Atici et al. (2015) expert rating list for distance from rivers and water bodies ranges from 250 meters to 3000 meters. We chose a median of 1500 meters for our analysis.	0.062
Distance to developed land	> 500 meters	Developed land cover includes both residential areas, which need distance away from the wind turbine due to the noise and visibility. Baban & Perry (2001) stated that the minimal optimal distance to residential dwellings would be 500 meters. This number will increase to around 2000 meters if near large settlements, but our analysis already excludes urban clusters and focus on rural	0.049

		communities. Therefore, we utilize 500 meters constraint in our analysis.	
Population density (1-mile radius clusters)	<500 ppl	For small-scale distributed wind energy systems across West Virginia, we also focus on rural communities that are not within urban clusters. USDA and the US census bureau define rural clusters as regions of fewer than 500 people per square mile (USDA,2020).	0.133
Power Outage percentage	>25%	This unique constraint specifically for our analysis will be shared across all three DG types, which helps us determine the high-energy-vulnerable regions that can be prioritized for new DG development.	0.028

3.53 Hydro DG Evaluation Criteria and Constraints

The core evaluation criteria in this study for the community-sized hydropower DG is the Feasible Small Project Sites (FSPS)datasets provided by NREL. FSPS datasets filtered potential feasible sites for small-scale hydropower development on a national level based on past analysis criteria (Department of Energy, 2013). We utilize these points datasets within West Virginia as our point of interest for our hydro DG development (Figure 6) and then apply our constraints unique to our DG suitability analysis. The hydropower DG infrastructures require streams and waterbodies to function. Therefore, we excluded all land covers for this specific DG development except the waterbodies from National Hydrology Datasets. Hydro DG also shares similar criteria compared to previous site feasibility analyses for solar and wind DG, such as population density, distance to substations, slopes, and power outage percentages.

Table 6-Hydro DG Evaluation Criteria and Constraints

Criteria	Constraints	Description/Source	Weight
Distance to FSPS	< 1600 meters	Department of Energy (2013) and Hall (2006) stated that the FSPS are located based on criteria within a 1-mile radius for optimal development. Therefore, we	0.283

		applied the 1600 meters constraint (1 mile).	
Population density (1-mile radius clusters)	< 500 people	The population density criteria are the same across our three DG suitability site analyses. We follow the USDA (2020) rural classification to locate communities with less than 2500 people and a density of fewer than 500 people per square mile.	0.172
Slope	< 10%	The slope of less than ten percent is generally considered economically feasible for construction (Ahmed et al., 2021) (Lu & Wang, 2017).	0.080
Distance to water source	<1600 meters	The distance to water sources varies among previous hydroelectricity studies depending on the scale of the project, which ranges from 1000 meters to 5000 meters. We applied the 1600 meters constraint similar to Yi et al. (2010)'s small hydropower analysis.	0.170
Distance to substation	< 6000 meters	We aim to keep economic criteria the same for our three types of DG infrastructures to keep them comparable. The 6000 meters is within an acceptable range for hydroelectricity (Ahmed et al., 2021).	0.073
Distance to protected areas	>2000 meters	Protected areas are the National Wildlife Refuges areas, West Virginia Wildlife Management areas, and National/Historical parks. The waterbodies through these areas are not suitable for hydropower development.	0.193
Power Outage percentage	>25%	The power outage constraint for our site suitability analysis helps us identify low-energy resilience areas. This criterion is a unique addition compared to existing geospatial analysis for new energy infrastructures.	0.03

Section 4 Net Value Comparison Analysis

4.1 LCOE/LACE with SCC for Distributed Generations

EIA updated LCOE and LACE yearly based on the changes in policies and technologies. We will employ the most recent EIA cost of energy suggestions as the foundation for this cost comparison analysis between different renewable energy types and existing coal energy. As mentioned before, LCOE refers to the estimated revenue required to develop and operate a specific energy generation facility, while LACE indicates the potential revenue available to that generation facility (EIA,2022). The Net Value for a generation facility can be calculated by subtracting LCOE from LACE or calculating the value cost ratio of LCOE to LACE. The cost comparison analysis in our study fundamentally follows the Net Value Equation (Equation 3). The cost comparison results can demonstrate whether the renewable DG facility is economically feasible compared to the existing coal energy. Therefore, positive outcomes from DG are critical to attracting future investment and development.

EIA 2022's Annual Energy Outlook provides the latest estimation of LCOE and LACE, including federal tax credits within the LCOE to certain renewable generation facilities to reduce the realized costs for these facilities (EIA, 2022). However, it is critical to note that EIA's cost estimations are projections for the future based on the currently available datasets and is possible to change due to future shifts in policies and technologies. Therefore, the averaged LCOE and LACE estimations used in our analysis also do not represent the exact costs and revenue for the future, and we only use the EIA estimations as references to accommodate future DG development. Our analysis will utilize the estimated LCOE and LACE values with tax credits with 2027 projections but without the social cost of carbon (Table 7 a, 7b). Then we will add the SCC to determine its impact on the costs(7c,7d). The SCC will be applied as 56$ per metric ton of carbon. According to EIA's Electricity Net Generation and Resulting CO_2 Emissions by Fuel Report in 2021, West Virginia coal-fired power plants' carbon emission rates ranked number 1 in the county and recorded 1933 pounds of CO_2 per MWh, which can be converted from pounds to 0.87 metric tons of CO_2 per MWh. Then we can compute the carbon emission costs per MWh by applying the SCC to the emission rate in West Virginia, which gave us 48.72 $ per MWh. The SCC value will be added to the cost of coal generation, whereas DG facilities can avoid the SCC and count it as a potential benefit with each MWh generated compared to conventional coal plants. The SCC value will increase the appeal and incentives for developing DG infrastructures.

Table 7a- Averaged LCOE/LACE estimations for new energies entering service in 2027

Unit $/megawatt-hour	DG Solar	DG wind (Onshore)	DG Hydro
LCOE	33.83	40.23	64.27
LACE	32.85	34.54	37.87
Net Value	-0.98	-5.69	-26.4
Value Cost Ratio	0.98	0.88	0.60

7b- Averaged existing coal energy costs and price ($/MWh)

LCOE for Coal	65
Current Electricity Price in WV (coal)	87.5
Net Value	22.5
Value Cost Ratio	1.34

7c- Averaged LCOE/LACE estimations for new energies entering service in 2027 with SCC

Unit $/megawatt-hour	DG Solar	DG wind (Onshore)	DG Hydro
LCOE	33.83	40.23	64.27
LACE	32.85	34.54	37.87
SCC	48.72	48.72	48.72
Net Value	47.74	43.03	22.32
Value Cost Ratio	2.4	2.06	1.34

7d- Averaged current coal energy costs and price with SCC ($/MWh)

LCOE for Coal	65
Current Electricity Price in WV (coal)	87.5
SCC	48.72
Net Value	-26.22
Value Cost Ratio	0.77

4.2 Community Size Net Value Combination Differences

West Virginia's DG suitability analysis mainly focuses on rural communities, so it is crucial to compare the potential net values from the DG with energy demands from different population sizes to determine the most economically feasible DG development plan. Rural classifications from USDA and the census bureau will be used to determine maximum population sizes for rural towns, and then we will reclassify rural communities into 500, 1000, 1500, 2000, and 2500 population sizes. The average annual electricity consumption per person in the US is 10632 Kilowatt-hours (KWh), which can be converted to 10.632 Megawatt-hours (MWh) (EIA, 2021). Then we can sum the average annual energy consumption with the designated population size to obtain the community's annual consumption. This statistic can assist us in computing the averaged MWh demand for our different rural populations (Table 8a). After obtaining the estimated annual electricity consumption for each community size, we can utilize the net dollar values from each DG type and existing coal generation to compare different generations' annual net values. Because our goal in this study is not to replace coal-fired power plants entirely but to recognize the partial development of distributed renewable energies to kickstart the future energy transition, we will introduce percentages of DG development and Coal to determine the most feasible combination for the near future.

Table 8a-Annual electricity demand by rural population size

Population	Annual Megawatt hour demand (MWh)
500	5316
1000	10632
1500	15948
2000	21264
2500	26580

Table 8b-Annual energy net values combination between coal and solar DG

Net Values for Energy supply Combination	5316 MWh	10632 MWh	15948 MWh	21264 MWh	26580 MWh	5316 MWh with SCC	10632 MWh with SCC	15948 MWh with SCC	21264 MWh with SCC	26580 MWh with SCC
DG solar 25% Coal 75%	88405.1	176810.2	265215.24	353620.32	446515.5	-41092.7	-82185.36	-123278.04	-164370.72	-205463.4
DG solar 50% Coal 50%	57200.16	114400.32	171600.48	228800.64	288906	57200.16	114400.32	171600.48	228800.64	286000.8
DG solar 75% Coal 25%	25995.5	51990.48	77985.72	103980.96	131296.5	155493	310986	466479	621972	777465

Table 8c-Annual energy net values combination between coal and wind DG

Net Values for Energy supply Combination	5316 MWh	10632 MWh	15948 MWh	21264 MWh	26580 MWh	5316 MWh with SCC	10632 MWh with SCC	15948 MWh with SCC	21264 MWh with SCC	26580 MWh with SCC
DG wind 25% Coal 75%	82145.49	164290.98	246436.47	328581.96	410727.45	-47352.27	-94704.5	-142057	-189409.08	-236761.35
DG wind 50% Coal 50%	44680.98	89361.96	134042.94	178723.92	223404.9	44680.98	89361.96	134042.94	178723.92	223404.9
DG wind 75% Coal 25%	7216.47	14432.94	21649.41	28865.88	36082.35	136714.23	273428.5	410142.7	546856.92	683571.15

Table 8d-Annual energy net values combination between coal and hydro DG

Net Values for Energy supply Combination	5316 MWh	10632 MWh	15948 MWh	21264 MWh	26580 MWh	5316 MWh with SCC	10632 MWh with SCC	15948 MWh with SCC	21264 MWh with SCC	26580 MWh with SCC
DG hydro 25% Coal 75%	54621.9	109243.8	163865.7	218487.6	273109.5	-74875.86	-149751.72	-224627.58	-299503.44	-374379.3
DG hydro 50% Coal 50%	-10366.2	-20732.4	-31098.6	-41464.8	-51831	-10366.2	-20732.4	-31098.6	-41464.8	-51831
DG hydro 75% Coal 25%	-75354.3	-150708.6	-226062.9	-301417.2	-376771.5	54143.46	108286.92	162430.38	216573.84	270717.3

The comparison analysis generated results based on the different population's energy demands. Each distributed generation facility, such as wind, solar, or hydro, has net values combined with coal generations to supply the annual energy demands for different community sizes. This analysis solely focuses on scenarios where DG facilities co-exist with coal-fired power plants and do not entirely replace them; thus, we only include frameworks with 25%, 50%, and 75% DG developments. A different framework is also included, which includes social carbon costs to subsidize the DG facilities, so they generate more net value and are more economically viable for development in the future. However, it is critical to note that the insertion of SCC is only a conceptualized scenario, which is possible to be applied in the future to reflect on GHG emission policies.

Section 5. Results

5.1 Solar DG Suitability Result

The AHP and pairwise comparison methods are highly effective for producing criteria weights for various DG resources, contributing to the validity of our spatial analytical framework. For this analysis, I referred to previous experts' analyses of physical and environmental constraints such as slope degrees, distance to energy grids, and distance from protected wildlife areas to validate our pairwise comparison and ensure accuracy and consistency in our weightings. However, our socio-economic constraints applied to small-scale DG development, such as population density and experienced outage percentages, were subjective and unique to rural West Virginia.

The weighted result of the pairwise comparison for solar DG is shown in table 4: solar irradiation (0.406), population density (0.192), distance to substation (0.155), slope (0.105), land use (0.101), and outages percentage (0.0401). To evaluate the consistency of our criteria weights, we calculated the Consistency Ratio (CR) that measures the consistency of the pairwise comparisons. A CR value less than 0.1 indicates an acceptable level of consistency, while a higher value indicates a flawed pairwise comparison. In such cases, the weighted sum analysis may produce meaningless results. Our solar DG site criteria yielded a CR value of 0.085, indicating a valid degree of consistency. The final solar DG suitable sites were generated using the weighted sum method and then classified into three categories by a natural break classification approach. The outcome includes low (0.336273-0.484263), medium (0.484263-0.578903), and high (0.578903-0.782203) suitability, respectively. During the fuzzy membership process, we removed non-suitable areas from the analysis, resulting in these areas being displayed with no colors on the output suitability map (Figure 8). Our multicriteria GIS solar model identified landscapes with little vegetation, such as barren land, shrubland, grassland, and some potential cultivated lands with pasture or pasture hay land types, as suitable areas for small solar DG systems. These land covers were found to be more economically viable and cost-effective for solar DG development than forest land covers, where trees and canopies can negatively impact solar resources.

From the output of the solar DG suitable sites, there are suitable sites scattered across the state, but it can be interpreted that most high suitability areas are located around eastern and southern counties (e.g., Berkeley, Grant, Greenbrier, Hardy, and Jefferson). This is likely due to the relatively high solar GHI found in these counties (Figure 4). Among the higher outage counties (Figure 7), Pocahontas County has the most potential to develop solar DG infrastructure to improve power outage issues, followed by Webster and Wayne counties with some highly suitable areas.

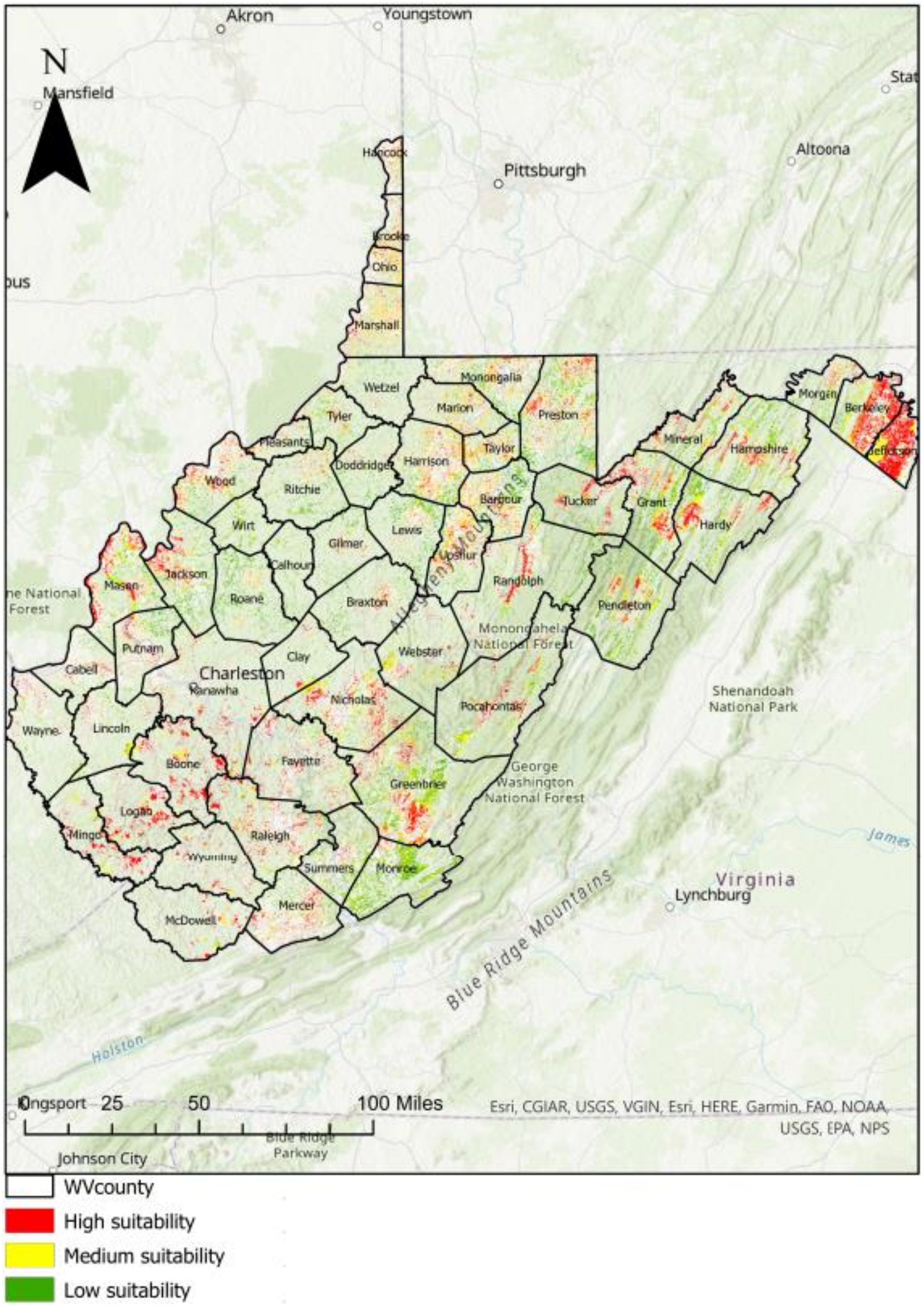

Figure 8-The suitability analysis for potential solar DG in West Virginia

5.2 Wind DG Suitability Result

Wind DG has more constraint criteria in this analysis due to increased risks and environmental hazards compared to other renewable resources (Baban & Parry, 2001). The weights of wind DG criteria are calculated by pairwise comparison (Table 5). Windspeed is the most crucial criterion in this analysis as it has the highest weight (0.282) and directly reflects the available wind energy resource. Distance to substation (0.173) and slope (0.119) are important technical and economic factors because they determine the cost-effectiveness of wind DG constructions. Locations with milder slopes of less than 10 degrees and closer to grids are considered more economically viable (Tegou & Haralambopoulos, 2010). Population density (0.133) allows us to identify accurate rural communities and filter out the urban populations. Distance to airport (0.081), distance to protected areas (0.072), distance to river/streams (0.062), and distance to developed land (0.049) serve similar roles in providing buffer areas to non-suitable areas and protect the local environment and ecosystem. The outage percentage (0.028) provides additional assessment by identifying areas that are highly vulnerable to energy outages. The consistent ratio result for wind DG criteria weights is 0.074 and smaller than 0.1, thus indicating the degree of consistency for our weights is considered valid for further GIS analysis.

The wind DG suitability analysis applied AHP and weight sum method and then reclassified into three categories by natural break classification: low (0.542814-0.617835), medium (0.617835-0.701513), and high (0.701513-0.955433) suitability. The fuzzy membership removed the unsuitable areas during the spatial reclassification process, which were displayed as the no-color areas on the suitability map (Figure 9). The multicriteria GIS analysis for wind DG was slightly more complicated due to the strict environmental constraints for wind turbine. We avoided all National Wildlife Refuges, West Virginia Wildlife Management Areas, and National/Historical parks to reduce any potential hazards that could affect wildlife and recreational areas.

The spatial result indicated that eastern and southern West Virginia have the highest wind DG development feasibility. More specifically, Pocahontas, Tucker, Grant, and Greenbrier counties had the most feasible sites for wind DG development according to our results. The existing wind farms located primarily in Tucker, Grant, and Greenbrier counties confirm the accuracy of our wind DG suitability analysis. However, the availability of land for new wind DG developments is limited due to the presence of already constructed wind farms in high-suitability areas. Among the counties with high outage rates, Pocahontas County has the most potential for future wind DG infrastructure, followed by Webster County.

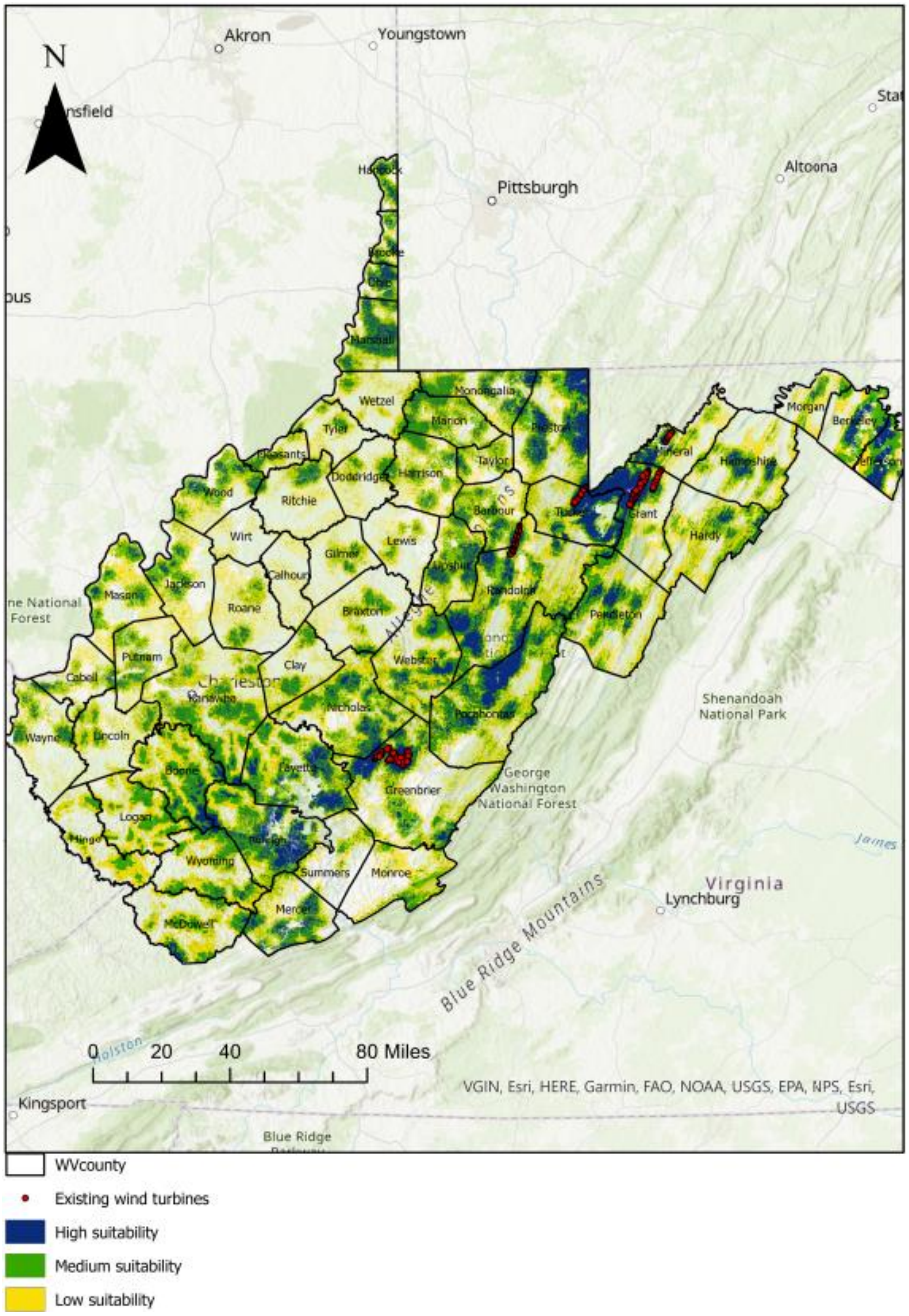

Figure 9-The suitability analysis for potential wind DG in West Virginia

5.3 Hydro DG Suitability Result

The multi-criteria GIS analysis of hydro DG heavily relies on the weights assigned to each criterion that was generated through the pairwise comparison method. These weights are essential for accurately assessing the suitability of potential hydro DG sites based on various physical, environmental, and socio-economic constraints. Among the criteria used, distance to FSPS weighted the heaviest (0.256), providing insights into potential locations for small hydropower facilities that generate less than 30MW. However, we acknowledged that the FSPS would not account for the unique characteristics of DG systems and the local environment in West Virginia. Thus, it is critical to incorporate additional criteria in the analysis to ensure a comprehensive evaluation of potential hydropower sites. We assigned weights to distance to substation (0.073), distance to water source (0.170), and slope (0.080) based on their known impact on reducing construction costs for hydropower facilities (Lu & Wang, 2017). To ensure the validity of our weights, we referenced similar weighted scores from previous small hydropower site suitability analyses, such as distance to water resources and energy grids, as conducted by Yi et al. (2010). Distance to protected areas (0.193) was found to be crucial in identifying unsuitable areas for hydropower development, specifically National Wildlife Refuges, West Virginia Wildlife Management areas, and National/Historical parks. For example, the New River Gorge National Park River section in Fayette County was part of the FSPS but filtered out after our GIS analysis. These areas that are highly sensitive to the local ecosystem, recreation, and tourism were not evaluated in the FSPS, underscoring the importance of considering the local context in spatial analysis. We then incorporated population density (0.172) and outage percentage (0.03) as part of our approach to prioritize low-population density rural communities with high occurrences of power outages for potential deployment of DG systems.

The consistency ratio result for our hydroelectricity criteria is 0.067, which is smaller than 0.1 and proves to be valid for consistency. We then proceed with the weighted sum method in GIS similar to previous solar and wind DG spatial analysis to generate the site suitability map (Figure 10). The hydropower DG suitability results were classified into three categories based on their suitability scores, namely low (0.455263-0.631448), medium (0.631448-0.807632), and high suitability (0.807632-0.983817). Since hydroelectricity generation facilities heavily rely on water bodies, all feasible sites were located in close proximity to rivers or other major water sources. While our analysis demonstrated varying potential for small hydropower across the state, we found that Clay, Lincoln, Webster, and Pocahontas counties showed promising feasibility for hydropower DG development, particularly in light of their higher power outage percentages.

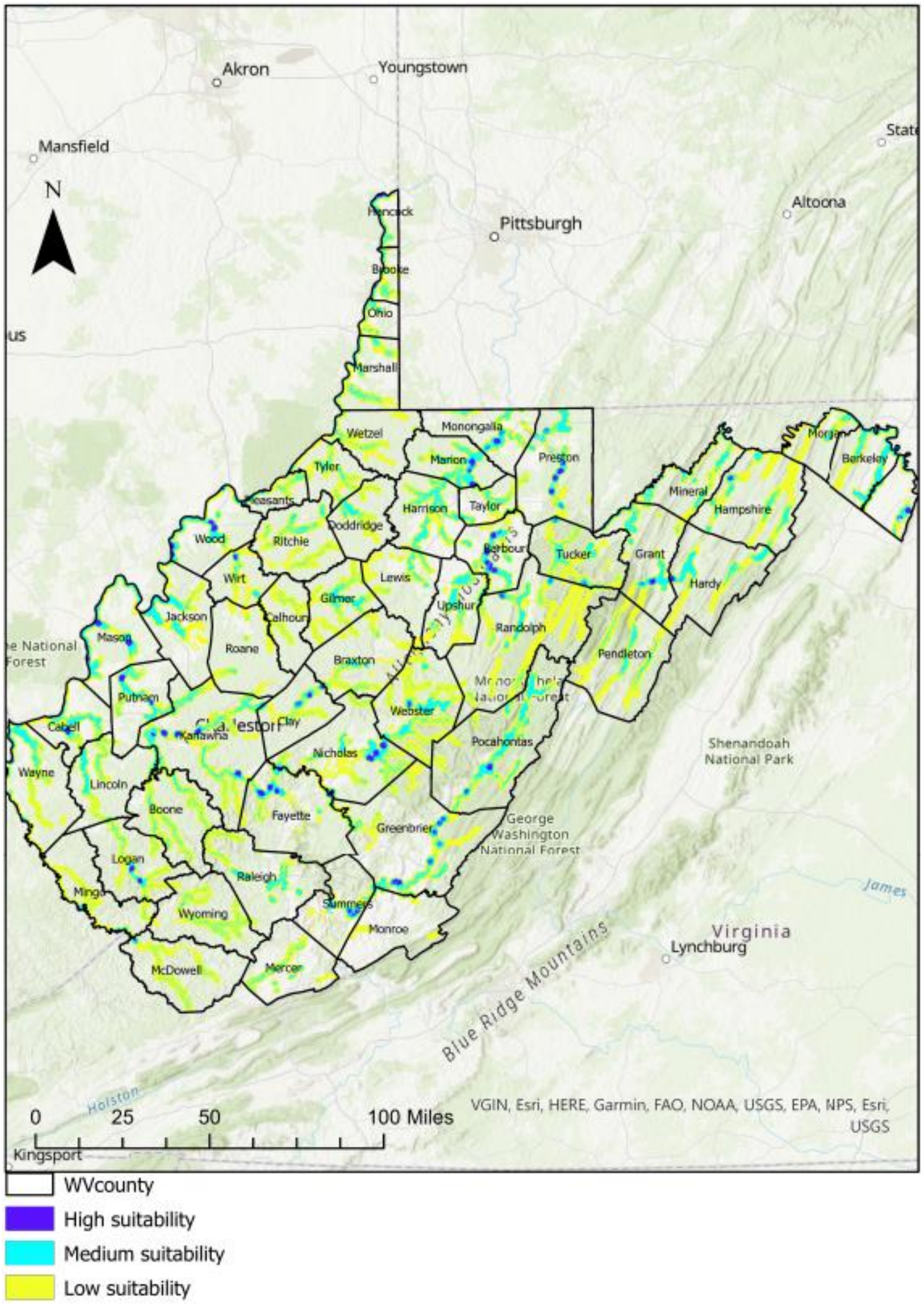

Figure 10-The suitability analysis for potential hydro DG in West Virginia

5.4 Sensitivity Analysis Results

The results of the sensitivity analysis were generated after conducting all three analyses on DG suitability, where all criteria were assigned equal weights to evaluate the robustness of our spatial analysis. The weighting approach used in our previous AHP pairwise comparisons may be susceptible to biases or errors, especially in the absence of established references on criteria weights for DG suitability analysis. The objective of the sensitivity analysis was to assess whether the locations identified as suitable for DG were impacted by the preference weights assigned to the criteria.

In the sensitivity analysis for solar DG, all criteria were given equal weights of 0.166. The resulting output map showed different feasible solar DG sites (Figure 11). We observed a significant reduction in highly suitable areas in West Virginia as compared to the original suitability map. However, in Pocahontas, Tucker, and Webster Counties, the solar DG suitability remained high in some areas, in contrast to the original suitability map results. Assigning equal weights to all criteria for solar DG downplayed the significance of solar irradiance strength, resulting a reduction in suitable areas in the eastern and southern regions. However, the equal weight method also highlighted the strong spatial feasibility of solar DG in the areas that remained high suitability after sensitivity analysis. The wind DG sensitivity analysis shared similar results when all criteria were given equal weights at 0.111. The high suitability areas for wind DG were reduced due to the decreased weight assigned to wind speed. Grant and Pocahontas Counties still displayed a significant presence of high suitable areas for wind DG, while the suitability areas were reduced in Raleigh County and increased in Webster County (Figure 12). The sensitivity analysis for hydropower DG demonstrated a similar trend of reducing the highly suitable areas across the state when all criteria were assigned equal weights of 0.142. However, due to the increased weight assigned to certain criteria, the medium and low suitability areas extended beyond water bodies and major rivers (Figure 13). Overall, the sensitivity analysis provided valuable additional perspectives to our AHP pairwise comparison weights. The suitable areas for all three types of DG in sensitivity analysis were considerably lower than original suitability analysis. However, the areas that overlapped in both results displayed more reliable potentials for future DG development. Notably, Pocahontas County demonstrated high suitability for all three types of DG compared to the rest of the state (Figure 11, 12 , and 13).

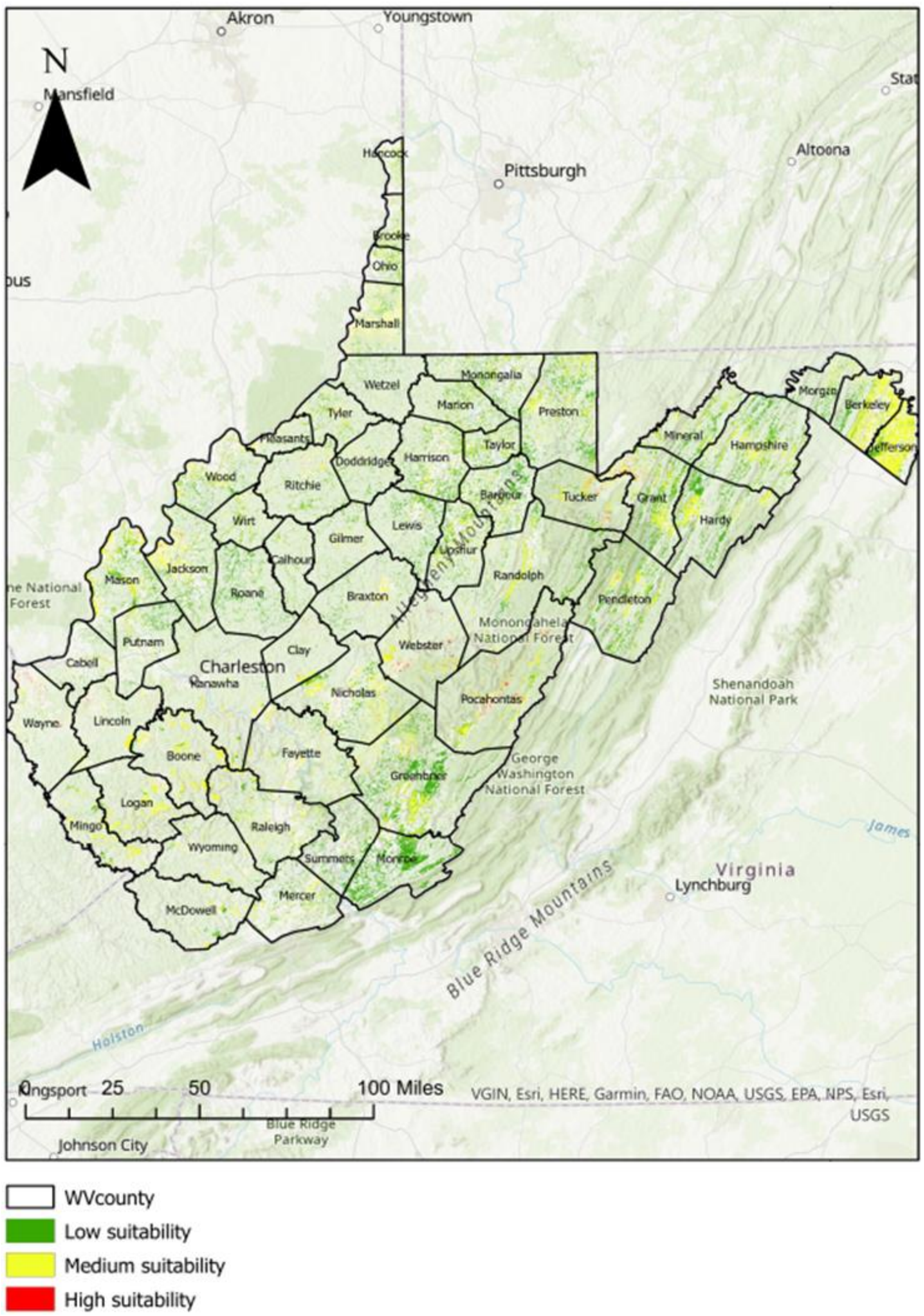

Figure 11-Solar DG Sensitivity analysis based on equal weight for each criterion

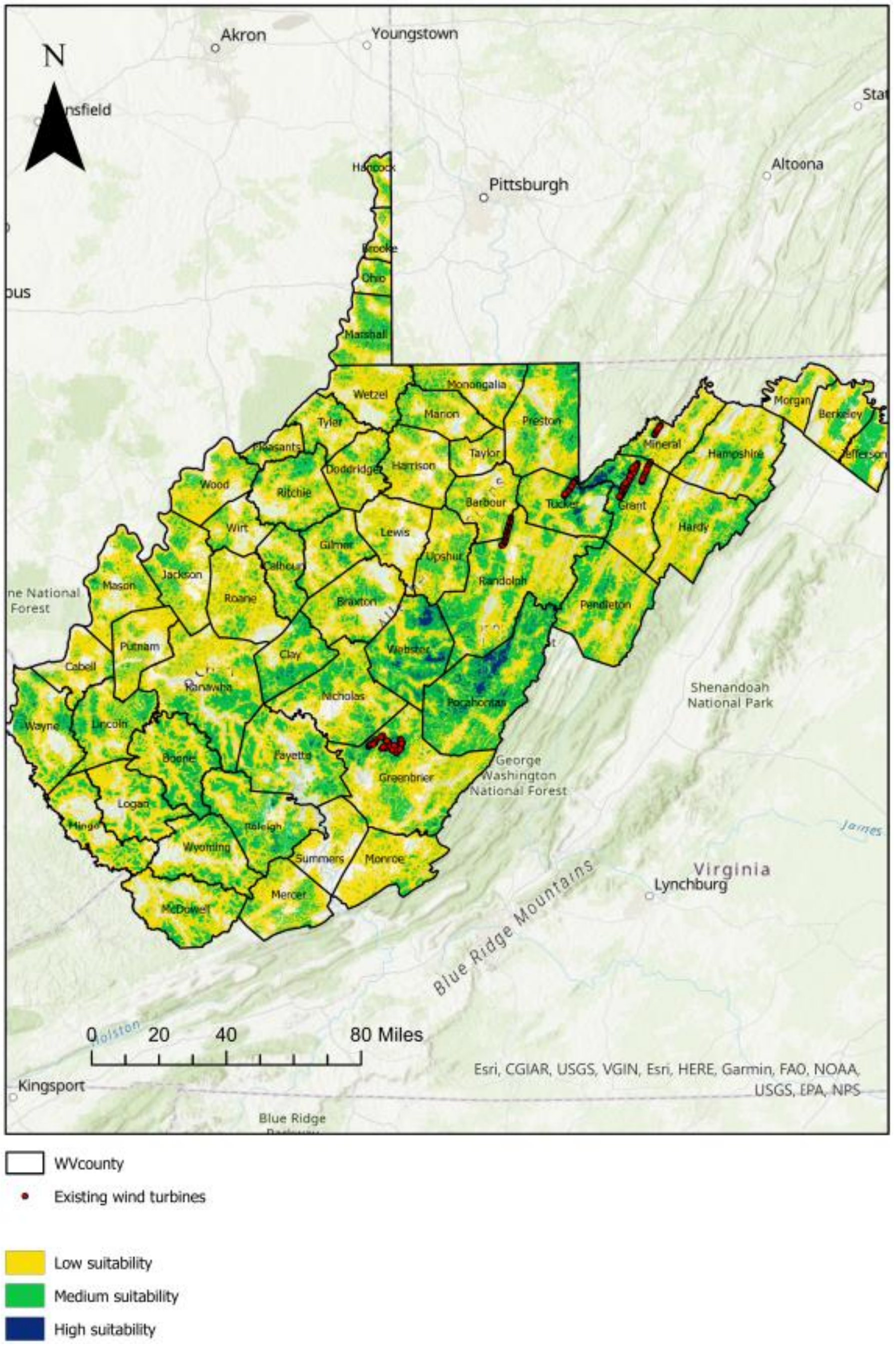

Figure 12-Wind DG Sensitivity analysis based on equal weight for each criterion

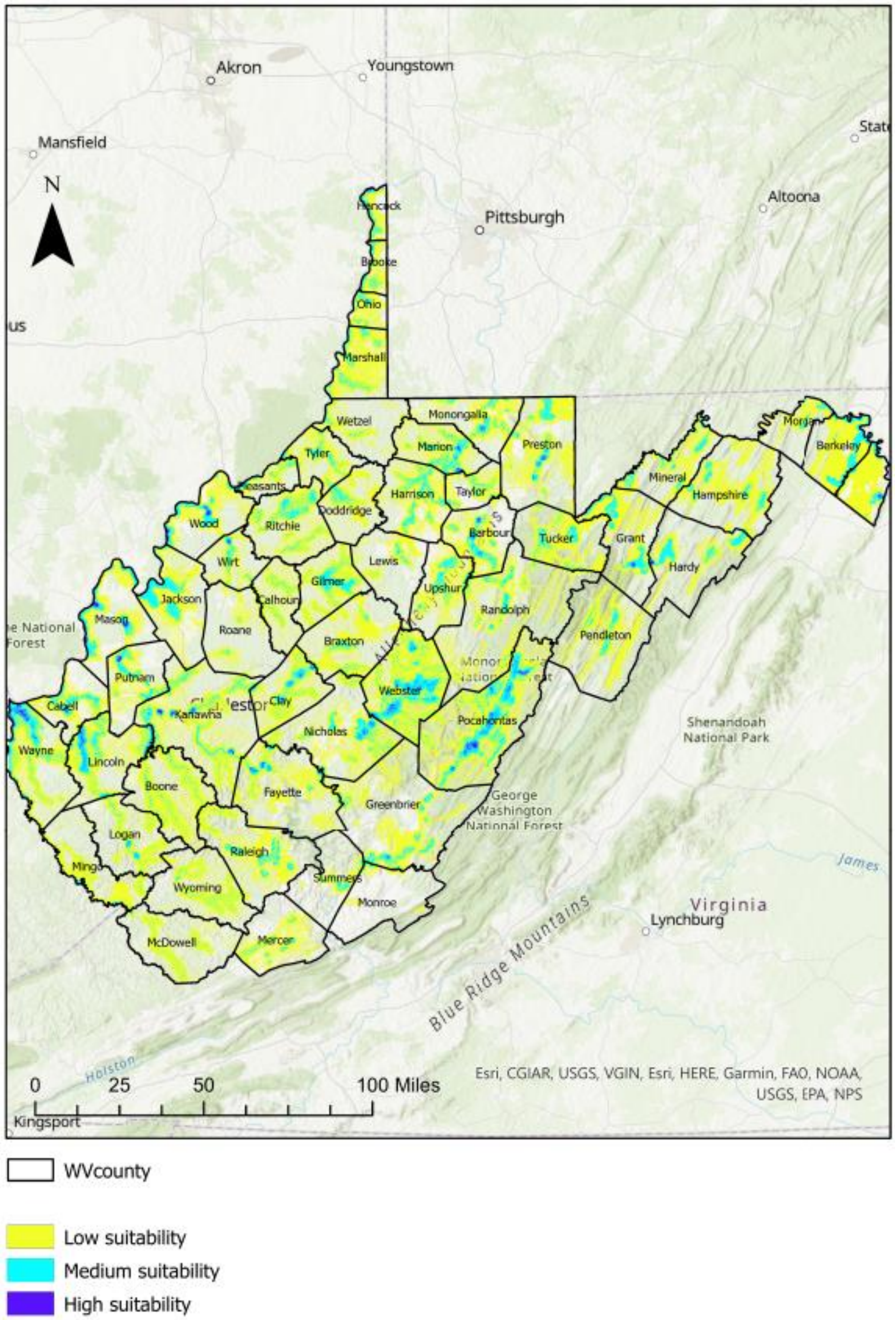

Figure 13-Hydro DG Sensitivity analysis based on equal weight for each criterion

5.5 Net Value Comparison Result

The net value comparisons were mainly conducted through LCOE and LACE values that were updated by EIA and applied to varied population sizes with different annual MWh demands in rural West

Virginia communities. We utilized the 2027 LCOE and LACE estimations to calculate the net values of all three renewable energy resource types in our study. The net value results of all three renewable energy resources had negative net values and value cost ratio less than 1 with solar (0.98), wind (0.88), and hydro (0.66). According to EIA, it is considered economically feasible when an energy source technology has a positive net value or an average value cost ratio greater than one. Negative net values reduce the incentives to develop renewable DG facilities. Therefore, to advocate DG infrastructure development in West Virginia, we first suggest the partial energy supply framework between coal-fired generation and DG facilities. We then introduce the SCC to further increase the appeal of DG by increasing the costs of coal-generated power.

The optimal net value results were divided into three parts, where each DG type was compared with coal-generated energy with different population energy demands (Table 8). The communities' populations of 500, 1000, 1500, 2000, and 2500 produced different combined net value results. Each comparison also had original net values and added SCC net values. Without SCC involvement, we observed that the highest and most optimal combined net values exist with the higher coal percentages in all DG/coal supply frameworks. On the other hand, when SCC was included in the analysis, the most economically viable supply percentages were reversed in favor of more DG due to the increased DG net value from avoiding SCC. Among the three DG types, solar had the most positive net values for all energy demand levels and was closely followed by wind generation, while hydropower DG had the most negative net values even with the addition of SCC due to its low economic return from generations.

Overall, the more populated rural areas had better net values due to the increase in MWh demands, leading to higher net value results. It is also considered more cost-effective to develop DG infrastructure that can generate power for as many people as possible instead focus on smaller communities. Suppose future DG development applies the non-SCC net values. It would be difficult to convince the decision-makers to invest and develop because of the low economic feasibility and negative net values. SCC net values results were more appealing than non-SCC net values. However, it is worth noting that SCC is not necessarily considered in West Virginia energy policy now. Our combined SCC net value framework result for different population sizes cannot be used as a finalized value-cost evaluation due to many factors we did not include other than LCOE and LACE. External factors and policy uncertainties pose significant challenges in providing reliable future projections and estimations. The estimation of LCOE and LACE by the EIA is updated annually, and future research must adjust to these changes.

5.6 Conclusion & Discussion

West Virginia exhibited promising renewable energy potentials and geospatial feasibility for all three types of renewable DG - solar, wind, and hydropower. Despite these potentials, various renewable energy resources in the state remained untapped. Most existing literature on energy development and planning lacked the incorporation of DG both in quantifiable models and spatial analyses. This scarcity may be attributed to the novelty of DG infrastructure and energy systems compared to traditional energy system and spatial planning. As a result, more future studies are needed to provide reference data for DG site suitability analyses.

This thesis employed AHP pairwise comparison combined with fuzzy logic and weighted sum methods to identify suitable locations for DG development in West Virginia. Environmental, socioeconomic, and technical factors were evaluated during the analysis. Although our analysis methods were effective in identifying spatially feasible sites for DG, the results were not without limitations. AHP pairwise comparison and weighted sum analysis relied on accurate criteria weight estimations, which can be challenging to determine. Previous GIS suitability studies have utilized past expert weights as references to ensure model accuracy. However, we had to rely on our subjective weight estimations for suitability criteria due to the scarcity of past DG site suitability analyses, especially with socio-economic criteria unique to rural West Virginia and DG systems. To ensure the consistency and accuracy of our weight estimations and evaluations, we conducted a consistency ratio test on our weights. The results of the CR test allowed us to determine the validity of our AHP pairwise comparison. Despite our efforts to minimize subjectivity in our data and analysis, there remained room for future improvement in objectivity. Increased involvement of the energy industry in DG suitability analysis could enhance objectivity and improve the accuracy of our results in the future with more experts' weights on suitability criteria.

Our study found that solar DG suitable sites were concentrated in the southern and eastern regions of West Virginia where solar radiation was higher. Jefferson, Berkely, Hardy and Greenbrier counties demonstrated promising sites for solar DG development (Figure 8). The recently developed solar energy infrastructure in Hardy County also validated our spatial analysis results (WVDN, 2022). The solar sensitivity analysis produced outcomes that exhibited fewer feasible sites in comparison to the original suitability analysis. Assigning equal weights to each criterion in the solar sensitivity analysis decreased the significance of the solar irradiance weight, resulting in a decrease of suitable sites in the eastern and southern regions of West Virginia where solar energy has a stronger presence. The reduction in suitable sites demonstrated the substantial impact of solar irradiance on site selection. However, the sensitivity analysis also revealed that Pocahontas, Tucker, and Webster Counties presented high suitable sites for solar DG development even after the decrease in solar irradiance weights (Figure 11). This implied that these areas have stronger and more consistent feasible sites for solar DG development. Additionally, it is worth noting that the total suitable land for solar DG was limited in this study as we focused on community-sized generation and did not include individual solar panels that could be installed on developed or residential land. The exclusion of individual solar DG systems was intended to standardize our spatial analysis and ensure comparability and consistency with the small community-scaled wind and hydropower DG. To broaden the scope of solar DG analysis, future research could include individual solar DG systems such as roof solar panels. This approach could enable a more specific and comprehensive assessment of solar DG feasibility in West Virginia.

The Wind DG suitability analysis revealed that all existing wind farms in West Virginia are situated in regions with high suitability, specifically in Tucker, Grant, Mineral, Randolph, and Greenbrier counties. The suitability analysis also identified other areas with high suitability for wind DG in Raleigh, Preston, and Pocahontas counties that have yet to see significant wind DG development. Particularly, Pocahontas County has a high outage rate and could benefit from improved energy resilience through DG development. The sensitivity analysis conducted for wind DG demonstrated that the development of wind DG in Pocahontas County remained viable, despite the overall decrease in the high suitability areas that resulted from assigning equal weights to all wind DG criteria (Figure 12). The reduction in high suitability areas was primarily due to the decreased weighting of wind speed and distance to the substation. Interestingly, Webster County showed a significant increase in high suitability results. This finding suggested that the increased impact of outage weights may have contributed to the observed trend. However, as noted in a previous study by Ajanaku et al. (2021), the lack of wind power development in Pocahontas County could be due to the expensive wind power permit applications required for National Forest land. While it is not impossible to construct wind turbines in the national forest, as evidenced by Vermont's wind farm construction, the cost of obtaining permits is an important factor that we did not consider in our spatial analysis. Beyond our suitability result, we recommend comparing additional expert criteria and weighted scores, if available, to further enhance the accuracy of the evaluation criteria. In future analyses, it would be valuable to explore more options and flexibilities for wind DG technologies and adaptations, particularly for small communities with lower energy demand. One possible improvement could be incorporating wind speed data at different surface heights, as using datasets ranging from 50 to 100 meters above the surface could produce different outputs than our input wind speed data at 80 meters.

Hydropower DG’s spatial suitability output showed fewer feasible locations compared to other two renewables. This can be attributed to the challenges posed by its water-dependent characteristics that limited the availability of suitable sites to major water bodies. The small hydroelectricity dataset also lacked locality information for West Virginia, thus required additional criteria to ensure the reliability of our spatial analysis results. For instance, the existing hydro dataset identified FSPS locations on New River in Fayette County. However, the recent establishment of a national park in the New River Gorge region rendered the previously collected hydro dataset inaccurate and made these regions unsuitable for any hydro DG development. To address this issue, we integrated additional environmental constraint layers into our GIS analysis to filter out areas unsuitable for development due to wildlife management and national park regulations, even if they were within feasible hydropower DG sites. The sensitivity analysis conducted for hydropower DG yielded results consistent with those obtained for solar and wind DG, with an overall decrease in high suitability areas. Despite the reduction in the overall suitability areas resulting from the sensitivity analysis, Pocahontas County remained the most feasible location for hydropower DG development. However, it is important to note that the sensitivity test output map generated using equal weights in the analysis could lead to potential inaccuracies in the results. Specifically, certain criteria, such as slope degree, received higher weights, leading to an increase in the number of medium and low suitability areas outside major river and water bodies. This highlighted the importance of employing appropriate AHP weights when evaluating the suitability sites for renewable DG development.

While our spatial analysis suggested that there were sufficient and feasible land areas for various new DG infrastructure development, there are still considerable numbers of impediments not accounted in our research that required additional time and improved studies specifically targeted at each DG system. To further enhance the spatial study, several extensions and external criteria could be incorporated, including assessing land ownership for DG infrastructure, considering permit costs for lands, evaluating public attitudes towards renewable energy, analyzing environmental policies, and examining the impacts of hydropower development on water quality standards and aquatic ecosystems. Additionally, identifying critical habitats for birds and bats near wind turbines can provide valuable insights into the ecological impacts of wind DG development. There is considerable scope for improving the DG suitability analysis by integrating MCDA technique and GIS analysis utilized in this study to focus on county-level analyses that provide more locality. Such analyses can provide more detailed results and insights into the optimal amount of land in each county suitable for future DG development. The AHP pairwise comparison weights used in this study could also be evaluated in different ways by adding or modifying criteria, a cross section of weights from more experts or engineers, and thus providing a more comprehensive and nuanced evaluation of the various factors affecting the geospatial feasibility for DG development.

In addition to geospatial feasibility for DG energy systems, economic feasibility is also crucial for the DG development decisions. Unlike the positive geospatial feasibility results, net value comparison analysis showed negative economic feasibility results for all DG types. This analysis indicated that developing DG facilities would not result in positive economic returns. Solar DG had the best economic incentives with a 0.98 value cost ratio, followed by wind at 0.88, and hydro at 0.66. When comparing DG to coal generation, the combined result shows that higher percentages of coal generation (75%) with lower percentages of DG (25%) result in the highest net values. The inclusion of SCC in the net value comparison analysis made a significant difference in all net value combination scenarios. The addition of SCC resulted in DG systems being more economically viable than previously indicated. Solar DG had the highest value cost ratio of 2.4, followed by wind at 2.06 and hydropower at 1.34. The combined highest net values of coal and DG energy were reversed, with the best economic incentives occurring when the percentage of DG was 75% and coal was 25%. Coal generation experienced the greatest reduction in net values under SCC scenarios due to increased costs for carbon emissions. Our study observed a correlation between the base rural population and net values. The economic returns were observed to increase with an increase in the rural population, while low-populated communities displayed lower energy consumption and consequently lower net values. Higher population densities lead to increased energy consumption rates, resulting in greater economic value for the energy infrastructure. Therefore, our net value results suggested prioritizing the development of DG systems in higher-populated rural areas. If spatial feasibility allows, solar DG presents the most promising option among the three DG types, as it has the highest net value return potential. Our analysis exclusively relied on the average national-level LCOE and LACE assessment. With additional time and resources, future studies could improve the reliability of economic comparisons by incorporating more localized datasets on LCOE and LACE.

An alternative to considering the social cost of carbon could be to include outage costs. Outage costs have a more direct impact on both customers and investors and should be considered in efforts to reduce costs, in addition to SCC. Lawton et al. (2003) estimated outage costs and found that the average outage costs across all seasons were around $3 per hour for residential customers and $1200 per hour for industrial customers. The significant financial impact of outages on the industrial sector in West Virginia, where energy consumption accounts for 46% (Figure 1), could provide greater motivation for the development of distributed generation compared to considering only residential outage costs. Including outage costs instead of SCC in net value comparisons could further incentivize DG development and could be a valuable addition to future analyses.

Given the significance of energy transition and its potential impact on rural West Virginia's socio-economic status and energy resilience, it is essential to explore the possibility of a distributed generation framework for rural communities to promote a transition from coal to more sustainable energy production and distribution. Our analysis provided site suitability analysis for distributed solar, wind, and hydropower energies by assessing environmental, socio-economic, and technical factors in rural West Virginia. It is important to note that our GIS outputs and net value comparison results do not represent final decisions on where to develop DG infrastructures, but this study laid a foundation for future DG development in West Virginia and can be applied as references and benchmarks for investors, developers, or government regulators. In summary, there are still many challenges to introducing wider usage of DG system, and the success of energy transition depends on many external factors other than spatial analysis. However, we believe there are tremendous opportunities and potentials for promoting the adaptation of DG energy infrastructure in West Virginia, which will ultimately benefit the state's long-term future.

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