task-1

May 15, 2025

1 Task 1: Exploratory Data Analysis (EDA)

[1]:
```python
# import required library
import pandas as pd

# read the dataset
df = pd.read_csv("PrimeFrontier_SolarDeploymentDataset.csv")

# check the first few rows
df.head()
```

[1]:
```
     Region  Solar_Irradiance_kWh_m2_day  Rural_Pop_Density_per_km2  \
0  Region_1                         6.00                         90
1  Region_2                         5.36                        206
2  Region_3                         6.15                         64
3  Region_4                         7.02                        350
4  Region_5                         5.27                        114

   Grid_Access_Percent  Infrastructure_Index  Electricity_Cost_USD_per_kWh  \
0                 23.0                  0.39                          0.31
1                 73.3                  0.88                          0.35
2                 28.3                  0.49                          0.36
3                 53.0                  0.22                          0.22
4                 35.1                  0.44                          0.37

   Terrain_Ruggedness_Score
0                      0.33
1                      0.55
2                      0.57
3                      0.98
4                      0.08
```

[2]:
```python
# Get a concise summary of the data
data_info = df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 7 columns):
```

```
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   Region                         50 non-null     object
 1   Solar_Irradiance_kWh_m2_day    50 non-null     float64
 2   Rural_Pop_Density_per_km2      50 non-null     int64
 3   Grid_Access_Percent            50 non-null     float64
 4   Infrastructure_Index           50 non-null     float64
 5   Electricity_Cost_USD_per_kWh   50 non-null     float64
 6   Terrain_Ruggedness_Score       50 non-null     float64
dtypes: float64(5), int64(1), object(1)
memory usage: 2.9+ KB
```

[3]:
```python
# Check for missing values
missing = df.isnull().sum()
missing
```

[3]:
```
Region                          0
Solar_Irradiance_kWh_m2_day     0
Rural_Pop_Density_per_km2       0
Grid_Access_Percent             0
Infrastructure_Index            0
Electricity_Cost_USD_per_kWh    0
Terrain_Ruggedness_Score        0
dtype: int64
```

[4]:
```python
# Check data types
data_types = df.dtypes
data_types
```

[4]:
```
Region                           object
Solar_Irradiance_kWh_m2_day     float64
Rural_Pop_Density_per_km2         int64
Grid_Access_Percent             float64
Infrastructure_Index            float64
Electricity_Cost_USD_per_kWh    float64
Terrain_Ruggedness_Score        float64
dtype: object
```

[5]:
```python
# Statistical summary for numerical data
summary_stats = df.describe()
summary_stats
```

[5]:
```
       Solar_Irradiance_kWh_m2_day  Rural_Pop_Density_per_km2  \
count                    50.000000                  50.000000
mean                      5.275200                 258.500000
std                       0.933235                 136.235578
min                       3.540000                  54.000000
```

```
25%                    4.637500                134.500000
50%                    5.270000                264.000000
75%                    5.832500                376.750000
max                    7.350000                498.000000

       Grid_Access_Percent  Infrastructure_Index  \
count            50.000000             50.000000
mean             52.816000              0.574800
std              20.202731              0.195242
min              20.000000              0.220000
25%              36.400000              0.407500
50%              50.750000              0.565000
75%              68.150000              0.747500
max              94.800000              0.900000

       Electricity_Cost_USD_per_kWh  Terrain_Ruggedness_Score
count                     50.000000                 50.000000
mean                       0.277800                  0.419800
std                        0.081323                  0.278732
min                        0.110000                  0.010000
25%                        0.212500                  0.220000
50%                        0.275000                  0.345000
75%                        0.357500                  0.602500
max                        0.400000                  0.980000
```

[6]:
```python
# Identify outliers using the IQR method
outliers_count = {}
for col in df.select_dtypes(include=['float64', 'int64']).columns:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    outlier_rows = df[(df[col] < (Q1 - 1.5 * IQR)) | (df[col] > (Q3 + 1.5 *␣
↪IQR))]
    outliers_count[col] = len(outlier_rows)

outliers_count
```

[6]:
```
{'Solar_Irradiance_kWh_m2_day': 0,
 'Rural_Pop_Density_per_km2': 0,
 'Grid_Access_Percent': 0,
 'Infrastructure_Index': 0,
 'Electricity_Cost_USD_per_kWh': 0,
 'Terrain_Ruggedness_Score': 0}
```

1.1 Data Cleaning Summary

Check	Result
Missing Values	None — all columns are complete
Data Types	All appropriate: floats, integers, and region names
Outliers	No statistical outliers detected using IQR method

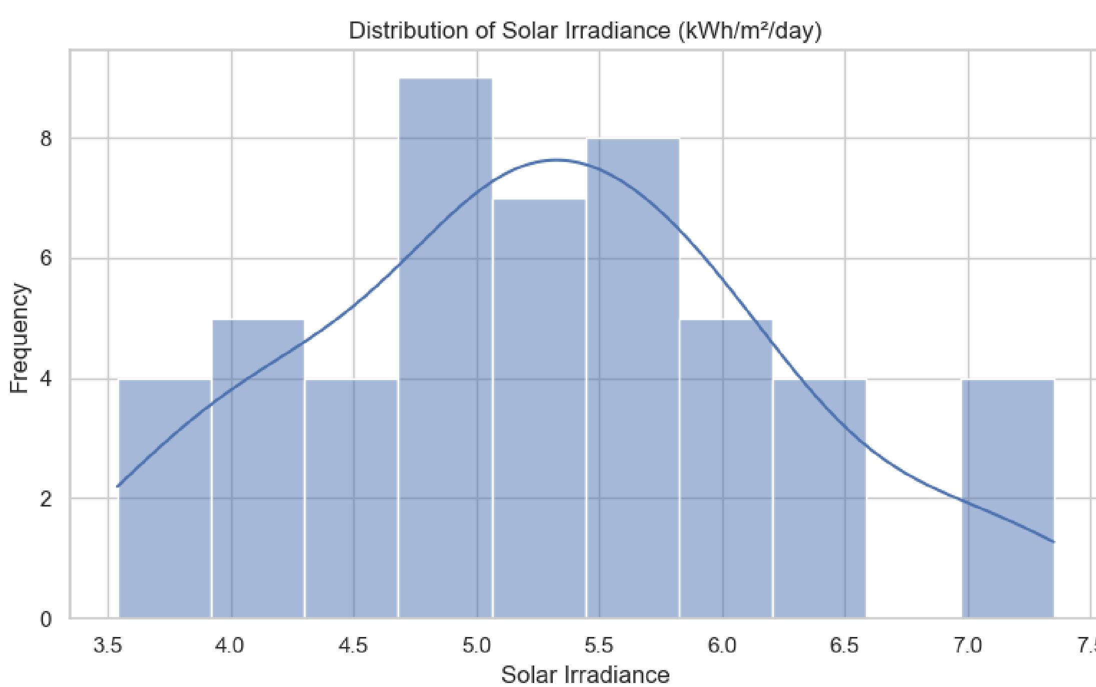
Conclusion: The dataset is clean and ready for exploratory analysis. No transformation is needed at this stage.

2 Visual Exploration

2.1 1. Histogram: Solar Irradiance

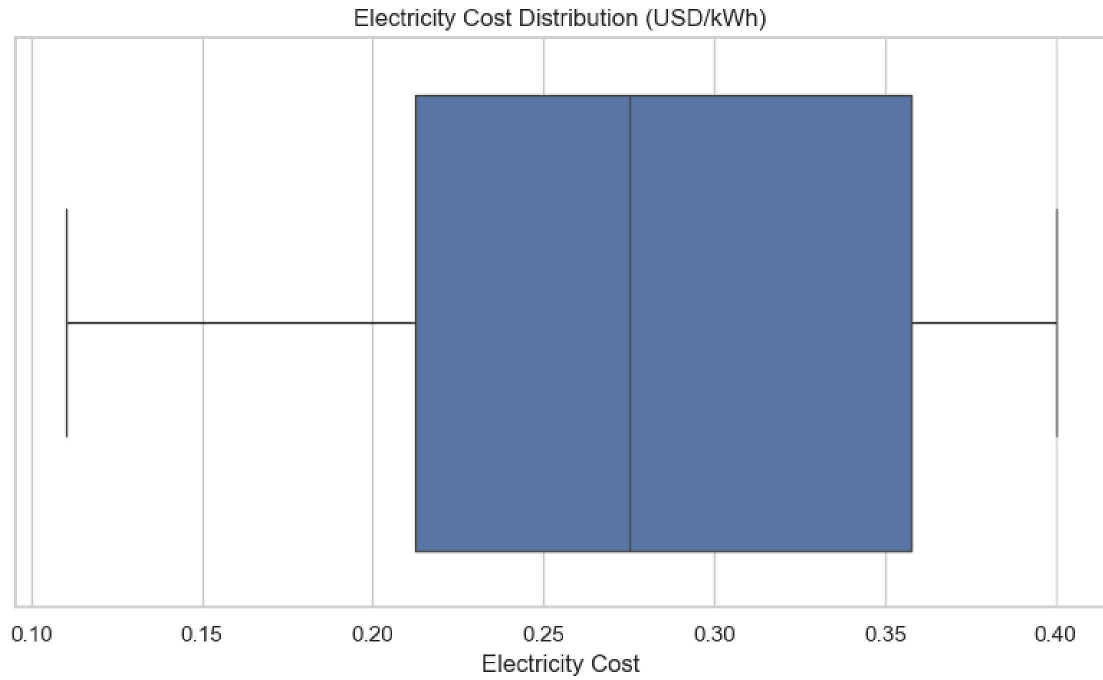
[7]:
```
# Set plot aesthetics
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="whitegrid")

# Histogram: Solar Irradiance
plt.figure(figsize=(8, 5))
sns.histplot(df['Solar_Irradiance_kWh_m2_day'], bins=10, kde=True)
plt.title('Distribution of Solar Irradiance (kWh/m²/day)')
plt.xlabel('Solar Irradiance')
plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```



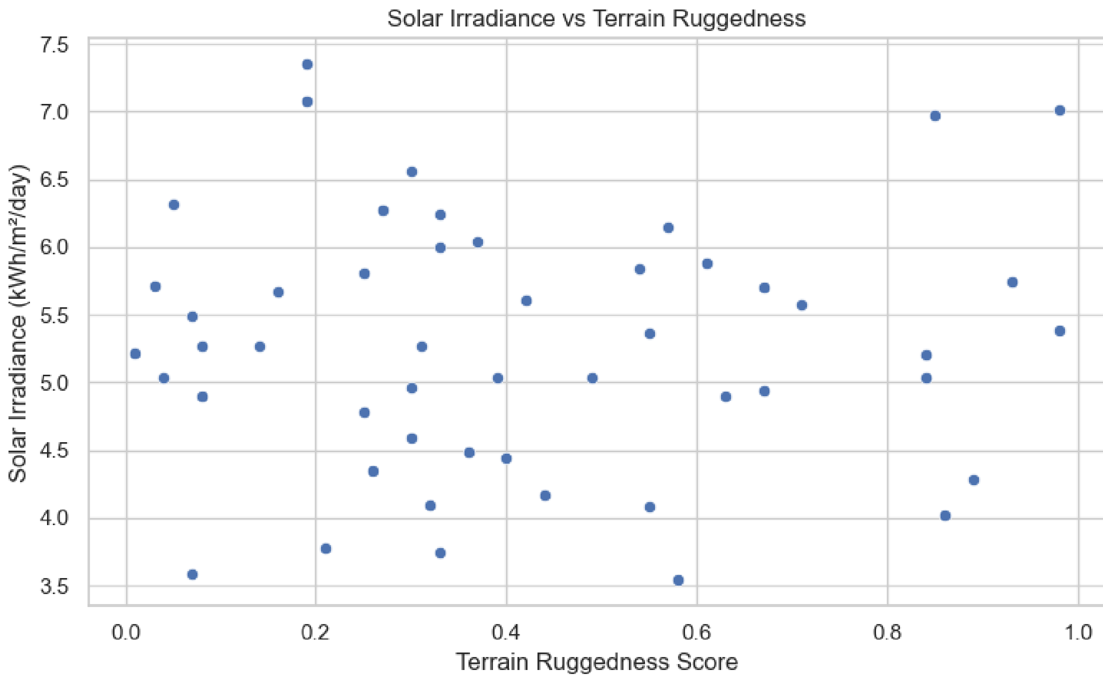
2.2 2. Boxplot: Electricity Cost

[8]:
```python
# Boxplot: Electricity Cost
plt.figure(figsize=(8, 5))
sns.boxplot(x=df['Electricity_Cost_USD_per_kWh'])
plt.title('Electricity Cost Distribution (USD/kWh)')
plt.xlabel('Electricity Cost')
plt.tight_layout()
plt.show()
```



2.3 3. Scatterplot: Terrain Ruggedness vs Solar Irradiance

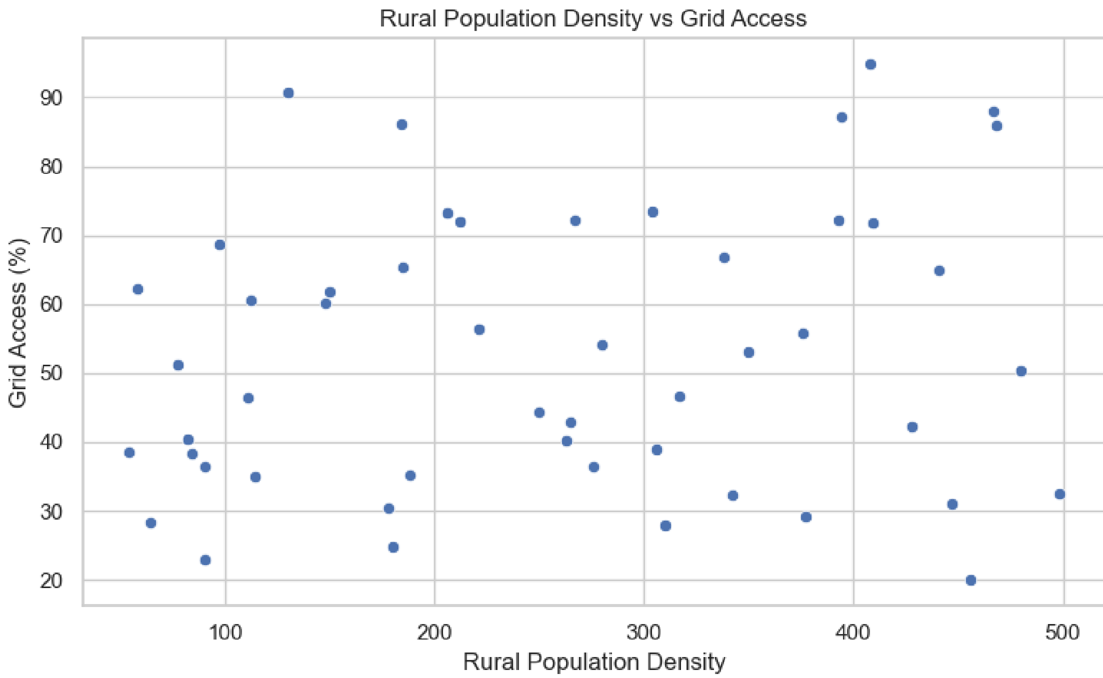
[9]:
```python
# Scatterplot: Terrain Ruggedness vs Solar Irradiance
plt.figure(figsize=(8, 5))
sns.scatterplot(data=df, x='Terrain_Ruggedness_Score',␣
 ↪y='Solar_Irradiance_kWh_m2_day')
plt.title('Solar Irradiance vs Terrain Ruggedness')
plt.xlabel('Terrain Ruggedness Score')
plt.ylabel('Solar Irradiance (kWh/m²/day)')
plt.tight_layout()
plt.show()
```



3 4. Scatterplot: Rural Pop. vs Grid Access

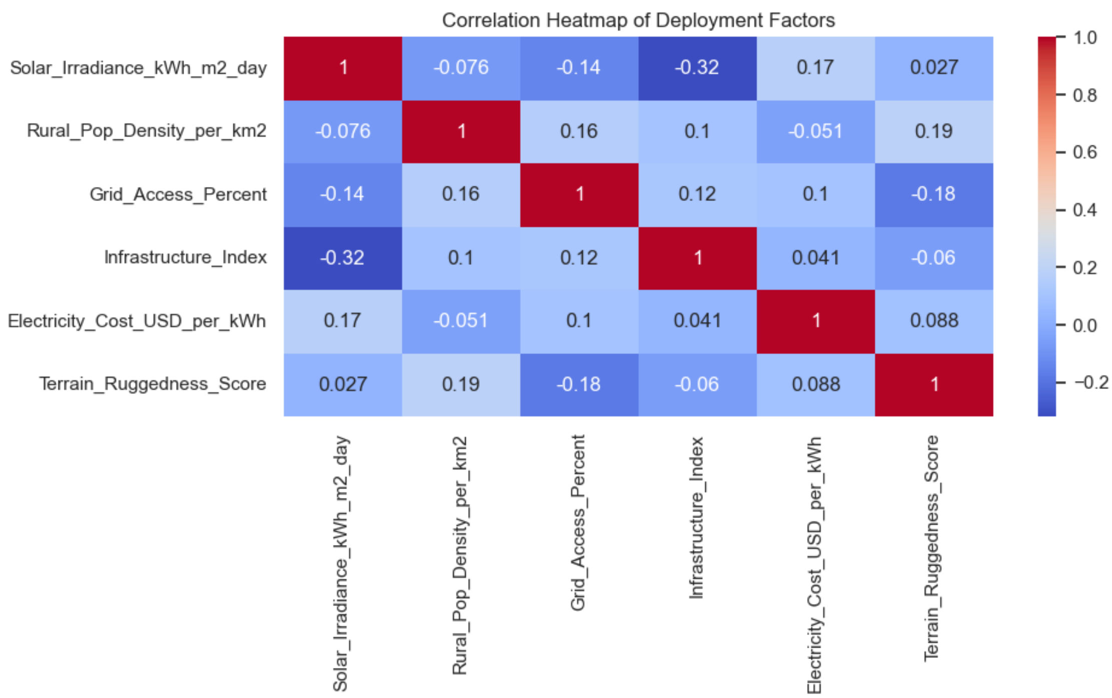
[10]:

```
# Scatterplot: Rural Pop. vs Grid Access
plt.figure(figsize=(8, 5))
sns.scatterplot(data=df, x='Rural_Pop_Density_per_km2', y='Grid_Access_Percent')
plt.title('Rural Population Density vs Grid Access')
plt.xlabel('Rural Population Density')
plt.ylabel('Grid Access (%)')
plt.tight_layout()
plt.show()
```



4 5. Heatmap: Correlation of Key Metrics

[11]:
```
# Heatmap: Correlation of Key Metrics
plt.figure(figsize=(10, 6))
sns.heatmap(df.drop(columns=['Region']).corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap of Deployment Factors')
plt.tight_layout()
plt.show()
```



4.0.1 Task 1 Summary: Key Insights & Red Flags

Insight 1: Solar Potential is High in Many Regions

- Solar irradiance spans from ~3.5 to 7.3 kWh/m²/day.
- Majority of regions cluster around 5.0–6.5, indicating generally favorable conditions.
- **Implication:** Regions with irradiance above 6.0 are prime candidates for immediate solar investment.

Actionable Suggestion: Flag the top 25% irradiance regions for detailed feasibility analysis.

Insight 2: High Energy Cost is a Real Barrier

- Electricity costs range from **$0.11 to $0.40/kWh**, with a mean of ~$0.28.
- Significant number of regions exceed the global average of $0.15–$0.20/kWh.
- **Implication:** High prices make solar an economically compelling alternative for rural areas.

Actionable Suggestion: we will use price sensitivity data to model consumer adoption curves in rollout planning.

Insight 3: Inverse Relationship Between Access & Need

- Terrain ruggedness is **negatively** correlated with infrastructure index and grid access.
- **High-ruggedness areas often lack grid coverage** and show high solar potential.
- **Implication:** These areas are underserved but technically feasible — ideal for off-grid or hybrid solar models.

Actionable Suggestion: Segment regions into:

- **On-grid augmentation zones**
- **Off-grid pilot zones**
- **Logistics-intensive but high-return zones**
