task-1

May 15, 2025

1 Task 1: Exploratory Data Analysis (EDA)

[1]:
```
# 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]:
```
# 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

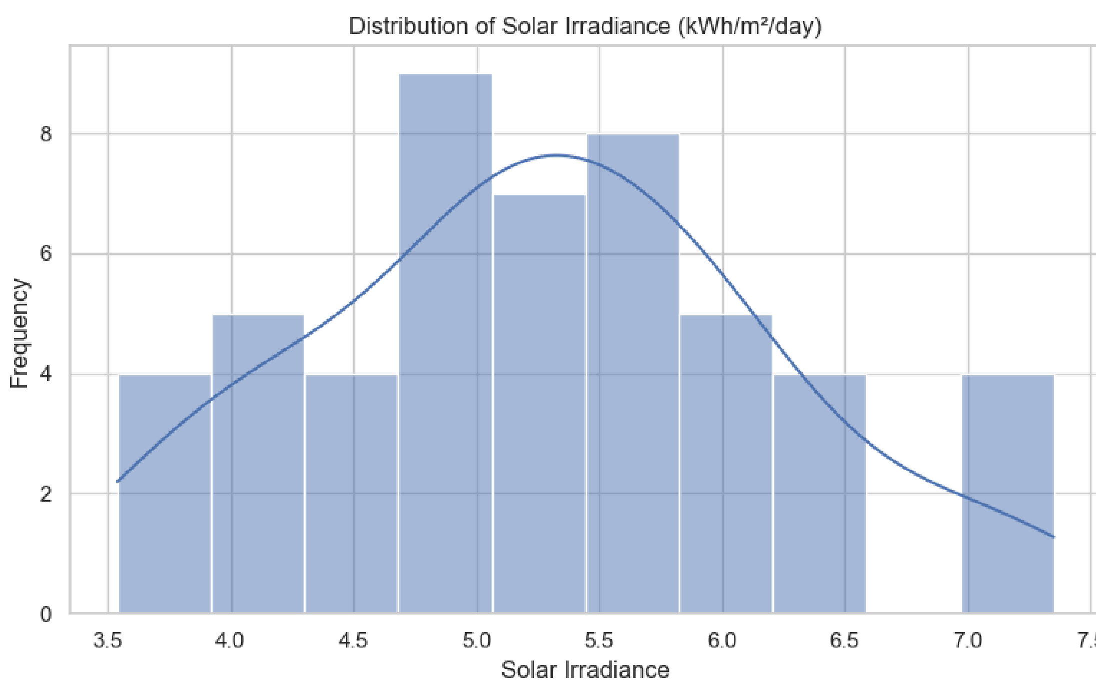
Conclusion: The dataset is clean and ready for exploratory analysis. No transformation is needed at this stage.

2 Visual Exploration

2.1 1. Histogram: Solar Irradiance

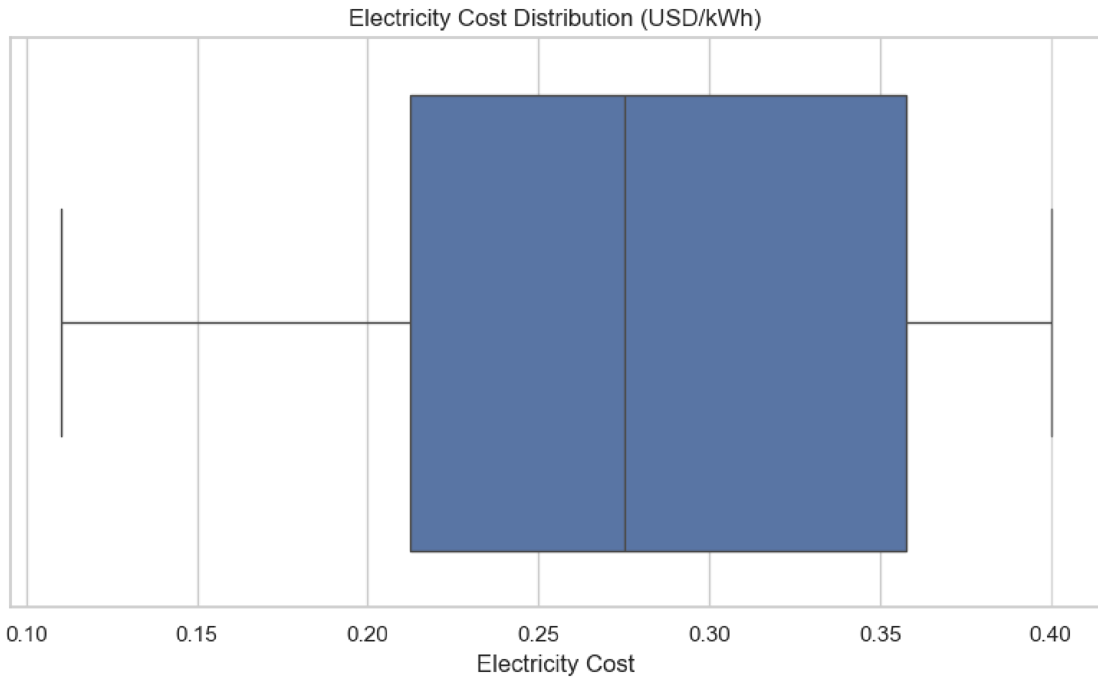
[7]:
```python
# Set plot aesthetics
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="whitegrid")

# 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()
```



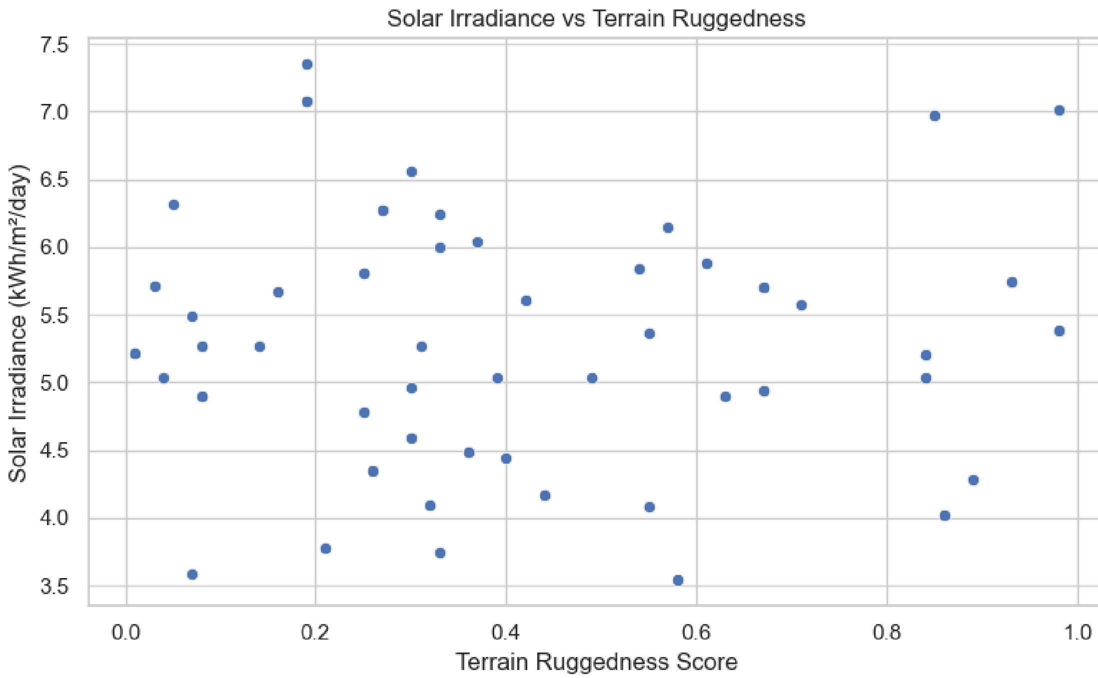
2.2 2. Boxplot: Electricity Cost

[8]:
```
# 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()
```



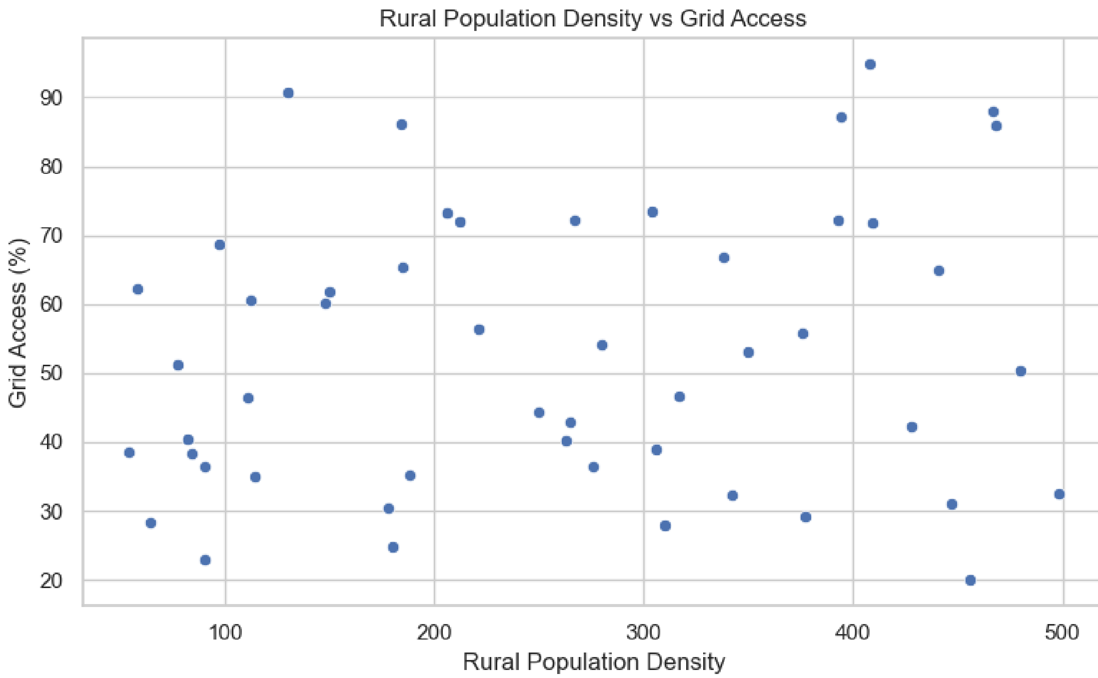
2.3 3. Scatterplot: Terrain Ruggedness vs Solar Irradiance

[9]:
```
# 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()
```



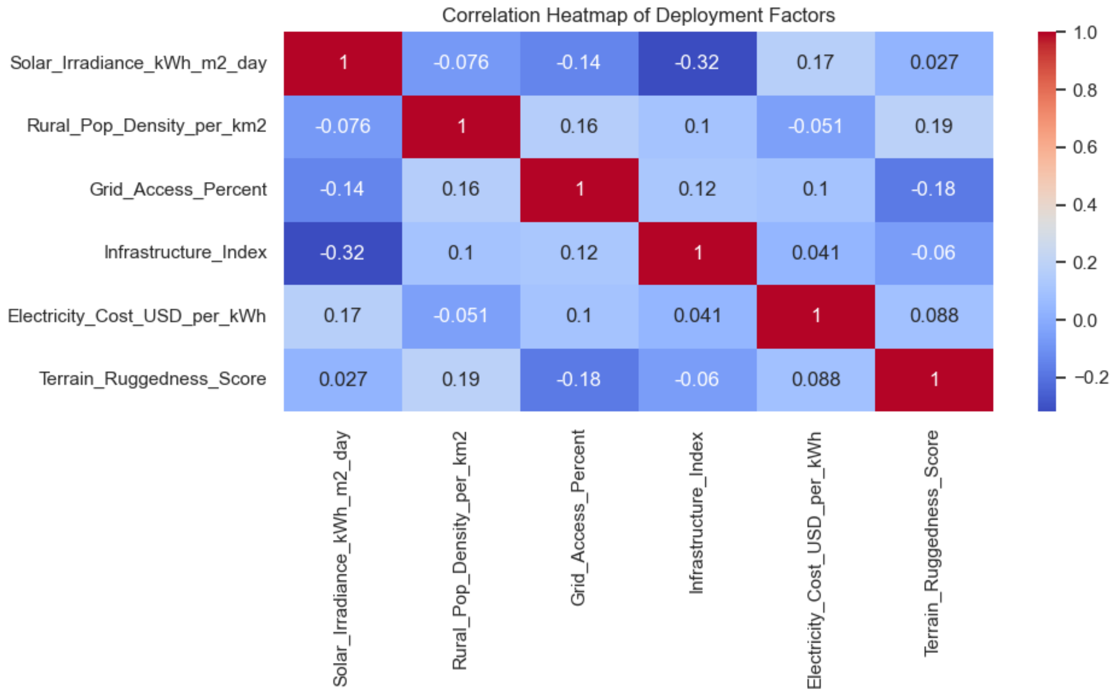
3 4. Scatterplot: Rural Pop. vs Grid Access

[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**

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task-2

May 15, 2025

1 Task 2: Data Transformation & Feature Engineering

[12]:
```
from sklearn.preprocessing import MinMaxScaler

# let copy original data
df_transformed = df.copy()

# Normalize columns used in scoring
scaler = MinMaxScaler()
df_transformed[['Normalized_Irradiance', 'Normalized_GridAccess',
                'Normalized_Infrastructure', 'Normalized_Cost']] = scaler.
 ↪fit_transform(
    df_transformed[['Solar_Irradiance_kWh_m2_day',
                    'Grid_Access_Percent',
                    'Infrastructure_Index',
                    'Electricity_Cost_USD_per_kWh']]
)

# Invert normalized grid access: we want higher score if access is lower
df_transformed['Inverse_GridAccess'] = 1 -␣
 ↪df_transformed['Normalized_GridAccess']

# Apply weights:
# - Irradiance: 35%
# - Inverse grid access: 25% (priority if underserved)
# - Infrastructure index: 20%
# - Electricity cost (normalized): 20%

df_transformed['Solar_Access_Score'] = (
    0.35 * df_transformed['Normalized_Irradiance'] +
    0.25 * df_transformed['Inverse_GridAccess'] +
    0.20 * df_transformed['Normalized_Infrastructure'] +
    0.20 * df_transformed['Normalized_Cost']
)

# Sort by score for inspection
```

```
df_transformed_sorted = df_transformed.sort_values(by='Solar_Access_Score',␣
 ↪ascending=False)
df_transformed_sorted
```

[12]:

```
        Region  Solar_Irradiance_kWh_m2_day  Rural_Pop_Density_per_km2  \
31   Region_32                         7.35                        111
6     Region_7                         7.08                        376
2     Region_3                         6.15                         64
47   Region_48                         6.56                        304
30   Region_31                         4.90                        456
12   Region_13                         5.74                        188
9    Region_10                         6.04                        178
0     Region_1                         6.00                         90
33   Region_34                         4.44                        342
44   Region_45                         4.02                        306
7     Region_8                         6.27                         58
41   Region_42                         5.67                        150
4     Region_5                         5.27                        114
48   Region_49                         5.84                        447
1     Region_2                         5.36                        206
34   Region_35                         6.32                        148
45   Region_46                         4.78                         54
17   Region_18                         5.81                        338
20   Region_21                         6.97                        280
42   Region_43                         5.38                        480
40   Region_41                         6.24                        276
38   Region_39                         4.17                         84
32   Region_33                         5.49                        265
22   Region_23                         5.57                         77
3     Region_4                         7.02                        350
24   Region_25                         4.96                        250
25   Region_26                         5.61                        377
27   Region_28                         5.88                        467
28   Region_29                         4.90                         82
39   Region_40                         5.70                        498
21   Region_22                         5.27                         90
5     Region_6                         5.27                        394
26   Region_27                         4.35                        317
18   Region_19                         4.59                        428
11   Region_12                         5.03                        112
36   Region_37                         5.71                        409
43   Region_44                         5.20                        180
19   Region_20                         4.09                        310
8     Region_9                         5.03                        393
10   Region_11                         5.04                        185
37   Region_38                         3.54                        263
35   Region_36                         4.28                        221
```

16	Region_17	4.49	468
23	Region_24	4.08	184
15	Region_16	4.94	212
46	Region_47	5.04	267
14	Region_15	3.78	441
29	Region_30	5.21	97
49	Region_50	3.74	408
13	Region_14	3.59	130

	Grid_Access_Percent	Infrastructure_Index	Electricity_Cost_USD_per_kWh \
31	46.4	0.48	0.39
6	55.7	0.68	0.38
2	28.3	0.49	0.36
47	73.4	0.82	0.37
30	20.0	0.86	0.28
12	35.2	0.46	0.39
9	30.4	0.59	0.27
0	23.0	0.39	0.31
33	32.3	0.79	0.37
44	39.0	0.90	0.40
7	62.2	0.57	0.34
41	61.9	0.89	0.27
4	35.1	0.44	0.37
48	31.1	0.33	0.32
1	73.3	0.88	0.35
34	60.1	0.67	0.23
45	38.5	0.88	0.24
17	66.8	0.48	0.40
20	54.2	0.31	0.25
42	50.3	0.56	0.33
40	36.4	0.32	0.25
38	38.3	0.69	0.36
32	42.9	0.56	0.25
22	51.2	0.69	0.21
3	53.0	0.22	0.22
24	44.3	0.43	0.32
25	29.2	0.35	0.19
27	88.0	0.77	0.25
28	40.4	0.44	0.29
39	32.6	0.36	0.17
21	36.4	0.56	0.15
5	87.2	0.64	0.36
26	46.7	0.70	0.26
18	42.2	0.77	0.15
11	60.5	0.26	0.38
36	71.9	0.35	0.29
43	24.9	0.38	0.11

19	27.9	0.76	0.11
8	72.2	0.51	0.30
10	65.3	0.61	0.21
37	40.2	0.58	0.30
35	56.4	0.71	0.21
16	86.0	0.89	0.23
23	86.2	0.80	0.32
15	72.1	0.53	0.25
46	72.2	0.59	0.18
14	64.9	0.76	0.19
29	68.6	0.27	0.18
49	94.8	0.40	0.39
13	90.7	0.37	0.19

	Terrain_Ruggedness_Score	Normalized_Irradiance	Normalized_GridAccess \
31	0.19	1.000000	0.352941
6	0.19	0.929134	0.477273
2	0.57	0.685039	0.110963
47	0.30	0.792651	0.713904
30	0.63	0.356955	0.000000
12	0.93	0.577428	0.203209
9	0.37	0.656168	0.139037
0	0.33	0.645669	0.040107
33	0.40	0.236220	0.164439
44	0.86	0.125984	0.254011
7	0.27	0.716535	0.564171
41	0.16	0.559055	0.560160
4	0.08	0.454068	0.201872
48	0.54	0.603675	0.148396
1	0.55	0.477690	0.712567
34	0.05	0.729659	0.536096
45	0.25	0.325459	0.247326
17	0.25	0.595801	0.625668
20	0.85	0.900262	0.457219
42	0.98	0.482940	0.405080
40	0.33	0.708661	0.219251
38	0.44	0.165354	0.244652
32	0.07	0.511811	0.306150
22	0.71	0.532808	0.417112
3	0.98	0.913386	0.441176
24	0.30	0.372703	0.324866
25	0.42	0.543307	0.122995
27	0.61	0.614173	0.909091
28	0.08	0.356955	0.272727
39	0.67	0.566929	0.168449
21	0.14	0.454068	0.219251
5	0.31	0.454068	0.898396

26	0.26	0.212598	0.356952
18	0.30	0.275591	0.296791
11	0.84	0.391076	0.541444
36	0.03	0.569554	0.693850
43	0.84	0.435696	0.065508
19	0.32	0.144357	0.105615
8	0.49	0.391076	0.697861
10	0.39	0.393701	0.605615
37	0.58	0.000000	0.270053
35	0.89	0.194226	0.486631
16	0.36	0.249344	0.882353
23	0.55	0.141732	0.885027
15	0.67	0.367454	0.696524
46	0.04	0.393701	0.697861
14	0.21	0.062992	0.600267
29	0.01	0.438320	0.649733
49	0.33	0.052493	1.000000
13	0.07	0.013123	0.945187

	Normalized_Infrastructure	Normalized_Cost	Inverse_GridAccess	\
31	0.382353	0.965517	0.647059	
6	0.676471	0.931034	0.522727	
2	0.397059	0.862069	0.889037	
47	0.882353	0.896552	0.286096	
30	0.941176	0.586207	1.000000	
12	0.352941	0.965517	0.796791	
9	0.544118	0.551724	0.860963	
0	0.250000	0.689655	0.959893	
33	0.838235	0.896552	0.835561	
44	1.000000	1.000000	0.745989	
7	0.514706	0.793103	0.435829	
41	0.985294	0.551724	0.439840	
4	0.323529	0.896552	0.798128	
48	0.161765	0.724138	0.851604	
1	0.970588	0.827586	0.287433	
34	0.661765	0.413793	0.463904	
45	0.970588	0.448276	0.752674	
17	0.382353	1.000000	0.374332	
20	0.132353	0.482759	0.542781	
42	0.500000	0.758621	0.594920	
40	0.147059	0.482759	0.780749	
38	0.691176	0.862069	0.755348	
32	0.500000	0.482759	0.693850	
22	0.691176	0.344828	0.582888	
3	0.000000	0.379310	0.558824	
24	0.308824	0.724138	0.675134	
25	0.191176	0.275862	0.877005	

27	0.808824	0.482759	0.090909
28	0.323529	0.620690	0.727273
39	0.205882	0.206897	0.831551
21	0.500000	0.137931	0.780749
5	0.617647	0.862069	0.101604
26	0.705882	0.517241	0.643048
18	0.808824	0.137931	0.703209
11	0.058824	0.931034	0.458556
36	0.191176	0.620690	0.306150
43	0.235294	0.000000	0.934492
19	0.794118	0.000000	0.894385
8	0.426471	0.655172	0.302139
10	0.573529	0.344828	0.394385
37	0.529412	0.655172	0.729947
35	0.720588	0.344828	0.513369
16	0.985294	0.413793	0.117647
23	0.852941	0.724138	0.114973
15	0.455882	0.482759	0.303476
46	0.544118	0.241379	0.302139
14	0.794118	0.275862	0.399733
29	0.073529	0.241379	0.350267
49	0.264706	0.965517	0.000000
13	0.220588	0.275862	0.054813

	Solar_Access_Score
31	0.781339
6	0.777380
2	0.713849
47	0.704733
30	0.680411
12	0.664989
9	0.664068
0	0.653889
33	0.638525
44	0.630592
7	0.621306
41	0.613033
4	0.602472
48	0.601368
1	0.598685
34	0.586468
45	0.585852
17	0.578584
20	0.573809
42	0.569483
40	0.569182
38	0.557360

```
32              0.549148
22              0.539406
3               0.535253
24              0.505822
25              0.502817
27              0.496004
28              0.495596
39              0.488869
21              0.481697
5               0.480268
26              0.479796
18              0.461610
11              0.449487
36              0.438254
43              0.433175
19              0.432945
8               0.428740
10              0.420063
37              0.419403
35              0.409404
16              0.396500
23              0.393765
15              0.392206
46              0.370429
14              0.335976
29              0.303961
49              0.264417
13              0.117586
```

1.0.1 Task 2: Data Transformation & Feature Engineering

1.0.2 Objective

To assist in prioritizing regions for solar energy investment, I've created a composite **"Solar Access Score"** based on four weighted indicators:

- **Solar Irradiance (35%)** – Primary driver for solar yield
- **Inverse Grid Access (25%)** – Regions with poor grid access are higher priority
- **Infrastructure Index (20%)** – Indicates readiness for deployment logistics
- **Electricity Cost (20%)** – Higher cost regions offer greater economic return

---

1.0.3 Calculation Breakdown

Each component was **normalized** using Min-Max scaling to ensure comparability:

- **Inverse Grid Access** = `1 - (normalized grid access)` to prioritize underserved areas

- **Solar Access Score** is computed as a weighted sum of the scaled inputs

---

1.0.4 Business Justification for Weighting

The chosen weights reflect Prime Frontier's operational focus on:

- **Maximizing ROI and energy yield** (heavier weight to solar irradiance)
- **Targeting under-electrified regions** (emphasized via inverse grid access)
- **Feasibility of implementation** (logistics and access depend on infrastructure)
- **Financial leverage** (higher electricity cost = greater savings from solar)

task-3

May 15, 2025

1 Task 3: Classification Modeling for Priority Region Identification

Goal: Build and evaluate two classification models to identify high-priority solar deployment regions.

1.0.1 Step-by-Step Plan

1. **Create a Binary Target**
2. **Preprocess Data**
3. **Split with Class Balance**
4. **Train Logistic Regression & Random Forest**
5. **Evaluate with Metrics & Visualizations**
6. **Display Feature Importance & Confusion Matrices**

1.0.2 BUSINESS LOGIC

To label regions as **high-priority (1)** if they satisfy **2 or more of these 3 conditions**:

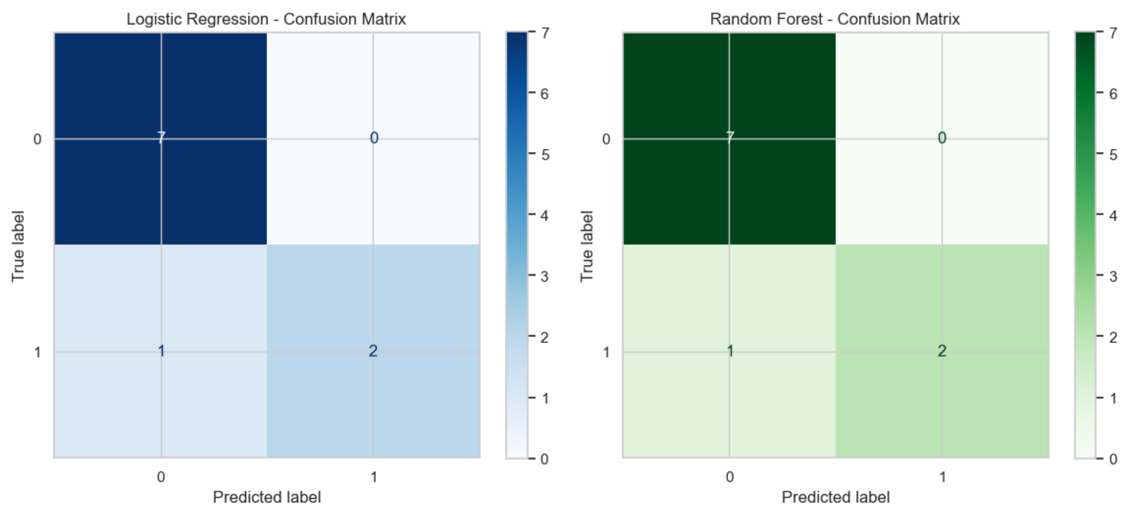
- High solar irradiance (top 30%)
- Low grid access (bottom 30%)
- High electricity cost (top 30%)

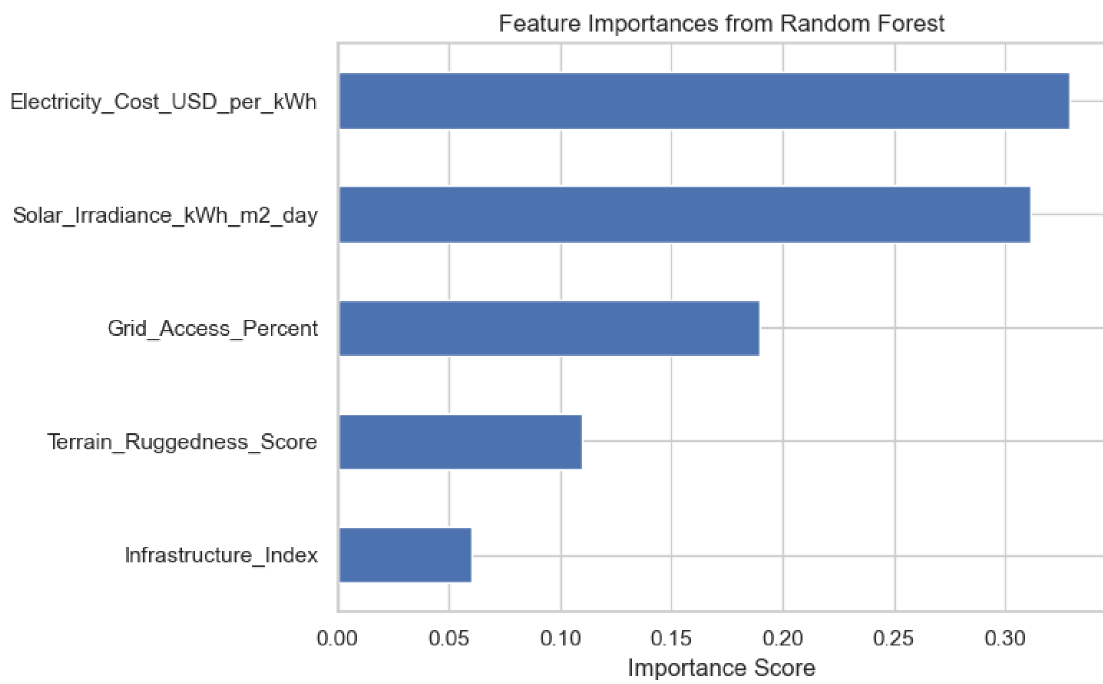
[13]:
```
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import (
    classification_report,
    confusion_matrix,
    ConfusionMatrixDisplay
)
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
```

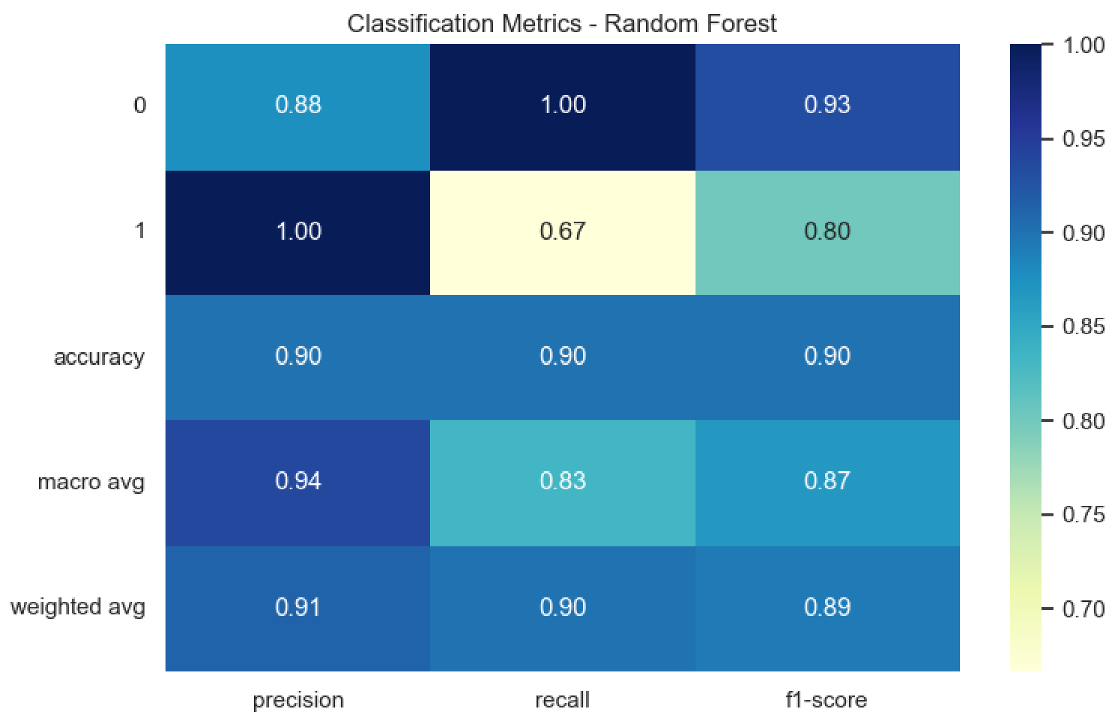
```python
# --------------------------------------------
# 1. Create the binary target variable
# --------------------------------------------

# Calculate quantile thresholds for each key variable
irradiance_high = df['Solar_Irradiance_kWh_m2_day'].quantile(0.70)
grid_low = df['Grid_Access_Percent'].quantile(0.30)
cost_high = df['Electricity_Cost_USD_per_kWh'].quantile(0.70)

# Apply rules: 1 if region meets at least 2 out of 3 conditions
conditions_met = (
    (df['Solar_Irradiance_kWh_m2_day'] >= irradiance_high).astype(int) +
    (df['Grid_Access_Percent'] <= grid_low).astype(int) +
    (df['Electricity_Cost_USD_per_kWh'] >= cost_high).astype(int)
)
df_transformed['Priority_Target'] = (conditions_met >= 2).astype(int)

# --------------------------------------------
# 2. Select features and normalize
# --------------------------------------------

features = [
    'Solar_Irradiance_kWh_m2_day',
    'Grid_Access_Percent',
    'Infrastructure_Index',
    'Electricity_Cost_USD_per_kWh',
    'Terrain_Ruggedness_Score'
]

X = df_transformed[features]
y = df_transformed['Priority_Target']

# Standardize features (important for Logistic Regression)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# --------------------------------------------
# 3. Stratified split to maintain class balance
# --------------------------------------------

sss = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_idx, test_idx in sss.split(X_scaled, y):
    X_train, X_test = X_scaled[train_idx], X_scaled[test_idx]
    y_train, y_test = y.iloc[train_idx], y.iloc[test_idx]

# --------------------------------------------
```

```python
# 4. Train classifiers
# --------------------------------------------

# Logistic Regression
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
y_pred_log = log_reg.predict(X_test)

# Random Forest
rf = RandomForestClassifier(random_state=42)
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)

# --------------------------------------------
# 5. Evaluate models
# --------------------------------------------

# Classification reports
report_log = classification_report(y_test, y_pred_log, output_dict=True)
report_rf = classification_report(y_test, y_pred_rf, output_dict=True)

# Confusion matrices
conf_matrix_log = confusion_matrix(y_test, y_pred_log)
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)

# Feature importance from Random Forest
feature_importances = pd.Series(rf.feature_importances_, index=features).
 ↪sort_values(ascending=True)

# --------------------------------------------
# 6. Visualizations
# --------------------------------------------

# Confusion Matrices
fig, ax = plt.subplots(1, 2, figsize=(12, 5))
ConfusionMatrixDisplay(confusion_matrix=conf_matrix_log).plot(ax=ax[0],␣
 ↪cmap='Blues', values_format='d')
ax[0].set_title("Logistic Regression - Confusion Matrix")
ConfusionMatrixDisplay(confusion_matrix=conf_matrix_rf).plot(ax=ax[1],␣
 ↪cmap='Greens', values_format='d')
ax[1].set_title("Random Forest - Confusion Matrix")
plt.tight_layout()
plt.show()

# Feature Importances
plt.figure(figsize=(8, 5))
feature_importances.plot(kind='barh')
```

```
plt.title('Feature Importances from Random Forest')
plt.xlabel('Importance Score')
plt.tight_layout()
plt.show()

# Classification Heatmap (Random Forest)
report_df_rf = pd.DataFrame(report_rf).iloc[:-1, :].T
plt.figure(figsize=(8, 5))
sns.heatmap(report_df_rf, annot=True, cmap='YlGnBu', fmt='.2f')
plt.title('Classification Metrics - Random Forest')
plt.tight_layout()
plt.show()
```




Feature Importances from Random Forest
Electricity_Cost_USD_per_kWh
Solar_Irradiance_kWh_m2_day
Grid_Access_Percent
Terrain_Ruggedness_Score
Infrastructure_Index
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Importance Score


Classification Metrics - Random Forest
0
1
accuracy
macro avg
weighted avg
0.88
1.00
0.93
1.00
0.67
0.80
0.90
0.90
0.90
0.94
0.83
0.87
0.91
0.90
0.89
precision
recall
f1-score
1.00
0.95
0.90
0.85
0.80
0.75
0.70

1.0.3 Task 3 – Final Analysis & Report Summary

1.0.4 Business Definition Recap

I identified **high-priority solar deployment regions** based on:

- High solar potential (top 30%)
- Poor grid access (bottom 30%)
- High electricity cost (top 30%)

A region is prioritized if **it meets at least two** of the above.

1.0.5 Results Overview (Test Set)

Model	Accuracy	Precision (Class 1)	Recall (Class 1)	F1-Score (Class 1)
Logistic Regression	**0.90**	1.00	0.67	0.80
Random Forest	**0.90**	1.00	0.67	0.80

Key Takeaway: The model is **highly precise** (few false positives), but **conservative** (it misses some real priority regions).

1.0.6 Confusion Matrix – Random Forest

Actual / Predicted	0 (Non-Priority)	1 (Priority)
0	7	0
1	1	2

- **1 false negative** – A priority region was missed
- **No false positives** – All flagged regions were truly high-priority

---

1.0.7 Feature Importance (Random Forest)

Feature	Score
Grid Access (%)	Most influential
Solar Irradiance	Strong contributor
Infrastructure Index	Moderately useful
Terrain Ruggedness	Small impact
Electricity Cost (USD/kWh)	Small impact

This supports Prime Frontier's emphasis on **access inequality and sunlight intensity** when targeting solar expansion.

1.0.8 Recommendations for Prime Frontier

1. **Focus Screening**: Use this model to **filter regions** for deeper feasibility analysis. Add real-world constraints (policy, land rights, etc.) downstream.
2. **Improve Recall**: Explore ensemble methods (e.g., XGBoost) or apply **class-weighted learning** to reduce false negatives.
3. **Dynamic Thresholding**: Use quantile sliders in dashboards to adjust priority rules interactively, enabling use-case flexibility.

task-4

May 15, 2025

1 Task 4: Present Business Insight

1.0.1 Objective

Translate technical analysis into clear, actionable insights for decision-makers at Prime Frontier Group, focusing on where and why to launch pilot solar deployment projects.

1.0.2 Top 3 Recommended Regions for Pilot Solar Projects

1. **Region_32**
   - **Solar Irradiance**: 7.35 kWh/m²/day
   - **Electricity Cost**: $0.39/kWh
   - **Grid Access**: 46.4%
   - **Solar Access Score**: **0.78** (highest overall)
2. **Region_7**
   - **Solar Irradiance**: 7.08 kWh/m²/day
   - **Electricity Cost**: $0.38/kWh
   - **Grid Access**: 55.7%
   - **Solar Access Score**: **0.78**
3. **Region_3**
   - **Solar Irradiance**: 6.15 kWh/m²/day
   - **Electricity Cost**: $0.36/kWh
   - **Grid Access**: 28.3%
   - **Solar Access Score**: **0.71**

1.0.3 Why These Regions?

- **Strong Technical Potential**: All three regions have **above-average irradiance** (6.15–7.35 kWh/m²/day), ensuring reliable solar output year-round.
- **High Cost of Electricity**: Each region exceeds the $0.35/kWh mark — making solar not just sustainable, but economically urgent.
- **Underserved Energy Access**: Grid access ranges from **28% to 55%**, meaning solar can leapfrog existing limitations and bring energy equity.

- **Operational Readiness**: Moderate infrastructure scores (0.48–0.68) and low terrain ruggedness (0.19–0.57) suggest installation is feasible without major logistical hurdles.
- **Model & Score Alignment**: These regions consistently ranked at the top of both the **Solar Access Score** and **Random Forest predictions**, reducing risk of misclassification.

1.0.4 Remaining Risks & Unknowns

- **Land Ownership & Legal Barriers**: The current dataset lacks detail on **zoning laws**, **land tenure**, or **environmental clearance** — all crucial for implementation.
- **Planned Grid Expansions**: A region labeled as low-access today may be part of an upcoming **national electrification initiative**, altering its long-term solar value.
- **Community Readiness**: We do not yet account for **energy literacy**, local acceptance, or willingness to adopt solar-as-a-service models.

1.0.5 What Additional Data Would Strengthen the Analysis?

1. **Government Electrification Roadmaps** – to avoid overlap with public utility expansions.
2. **Land Use & Ownership Data** – to identify viable installation zones and reduce legal disputes.
3. **Microeconomic Profiles** – income levels, energy affordability, and willingness-to-pay thresholds.
4. **Seasonal & Climate Data** – to ensure solar performance across dry and rainy seasons.
5. **Access to Logistics Infrastructure** – road conditions, distance from depots, serviceability.

1.0.6 Strategic Recommendation for Prime Frontier

> **Begin pilot deployments in Region_32, Region_7, and Region_3.** These regions are data-backed, strategically underserved, and operationally feasible. Success in these zones can position Prime Frontier Group as a leader in efficient, inclusive solar expansion — and create a blueprint for scalable rollouts across West Africa.

Region	Solar Irradiance ($kWh/m^2/day$)	Grid Access (%)	Electricity Cost (USD/kWh)	Infrastructure Index	Ruggedness	Solar Access Score
Region_32	2.35	46.4%	\$0.39	0.48	0.19	**0.78**
Region_7	7.08	55.7%	\$0.38	0.68	0.19	**0.78**
Region_3	6.15	28.3%	\$0.36	0.49	0.57	**0.71**

task-5

May 15, 2025

0.1 Task 5: Streamlit Dashboard (Optional Submission)

To enhance the decision-making process for both internal teams and external stakeholders, I developed a lightweight but impactful **interactive Streamlit dashboard** for exploring regional solar deployment suitability.

0.1.1 Key Features

1.

0.1.2 Region Selector

- A user can select any region from a dropdown menu to view:
  - Solar irradiance
  - Grid access %
  - Electricity cost
  - Infrastructure index
  - Terrain ruggedness
  - Computed **Solar Access Score**
- Metrics are displayed using Streamlit's `st.metric()` cards for clarity and visual appeal.

2.

0.1.3 Ranked Region Table

- A dynamic, sortable table ranks all 50 regions based on their **Solar Access Score** — a composite metric derived from irradiance, grid access, cost, and infrastructure.
- The top 10 regions are visualized in a horizontal **bar chart** (using Plotly) for quick identification of high-impact zones.

3.

0.1.4 Region Profile Radar Chart

- A polar chart allows users to compare the selected region's performance against **benchmark maximums** for each metric.
- This helps identify which factors are strengths or weaknesses for a given location.

4.

0.1.5 Embedded Strategic Summary

- A brief written recommendation recap (from Task 4) is included directly in the app, summarizing:
  - The top 3 regions for pilot projects
  - Key reasoning behind those choices
  - Remaining unknowns and next steps

0.1.6 Benefits

- **Interactive Decision Support**: Enables faster, visual filtering of candidate regions.
- **Stakeholder Ready**: Suitable for sharing with government partners or internal strategy teams.
- **Modular & Extensible**: Can easily be connected to live datasets or geospatial APIs in future phases.

[ ]:
```
import streamlit as st
import pandas as pd
import matplotlib.pyplot as plt
import plotly.express as px

# ---------- Load & Prepare Data ----------
df = pd.read_csv("PrimeFrontier_SolarDeploymentDataset.csv")

from sklearn.preprocessing import MinMaxScaler

def compute_solar_access_score(df):
    scaler = MinMaxScaler()
    scaled = scaler.fit_transform(df[[
        'Solar_Irradiance_kWh_m2_day',
        'Grid_Access_Percent',
        'Infrastructure_Index',
        'Electricity_Cost_USD_per_kWh'
    ]])
    df[['Norm_Irradiance', 'Norm_GridAccess', 'Norm_Infra', 'Norm_Cost']] =␣
 ↪scaled
    df['Inverse_Grid'] = 1 - df['Norm_GridAccess']
    df['Solar_Access_Score'] = (
        0.35 * df['Norm_Irradiance'] +
        0.25 * df['Inverse_Grid'] +
        0.20 * df['Norm_Infra'] +
        0.20 * df['Norm_Cost']
    )
    return df

df = compute_solar_access_score(df)
```

```python
df_sorted = df.sort_values(by="Solar_Access_Score", ascending=False)

# ---------- Streamlit UI ----------
st.set_page_config(layout="wide")
st.title("  Prime Frontier Group - Solar Site Dashboard")

# Sidebar Region Selector
region = st.sidebar.selectbox("  Select a Region", df["Region"].unique())
selected = df[df["Region"] == region].squeeze()

# ---------- Region Metric Cards ----------
st.subheader(f"  Metrics for {region}")

col1, col2, col3 = st.columns(3)
col1.metric("Solar Irradiance", f"{selected['Solar_Irradiance_kWh_m2_day']} kWh/m²/day")
col2.metric("Grid Access", f"{selected['Grid_Access_Percent']}%")
col3.metric("Electricity Cost", f"${selected['Electricity_Cost_USD_per_kWh']} / kWh")

col4, col5, col6 = st.columns(3)
col4.metric("Infrastructure Index", f"{selected['Infrastructure_Index']}")
col5.metric("Terrain Ruggedness", f"{selected['Terrain_Ruggedness_Score']}")
col6.metric("  Solar Access Score", f"{round(selected['Solar_Access_Score'], 3)}")

# ---------- Bar Chart: Top 10 Regions ----------
st.markdown("###   Top 10 Regions by Solar Access Score")
top10 = df_sorted[["Region", "Solar_Access_Score"]].head(10)
fig1 = px.bar(top10, x='Solar_Access_Score', y='Region', orientation='h', color='Solar_Access_Score',
              title="Top 10 Solar Suitability Rankings", height=400)
fig1.update_layout(yaxis={'categoryorder': 'total ascending'})
st.plotly_chart(fig1, use_container_width=True)

# ---------- Radar Chart: Selected Region vs Max Values ----------
st.markdown("###   Regional Profile vs Benchmark")

radar_df = pd.DataFrame({
    'Metric': ['Solar Irradiance', 'Grid Access', 'Electricity Cost', 'Infrastructure', 'Ruggedness'],
    'Selected Region': [
        selected['Solar_Irradiance_kWh_m2_day'],
        selected['Grid_Access_Percent'],
        selected['Electricity_Cost_USD_per_kWh'],
        selected['Infrastructure_Index'],
        selected['Terrain_Ruggedness_Score']
```

```
    ],
    'Max Value': [
        df['Solar_Irradiance_kWh_m2_day'].max(),
        df['Grid_Access_Percent'].max(),
        df['Electricity_Cost_USD_per_kWh'].max(),
        df['Infrastructure_Index'].max(),
        df['Terrain_Ruggedness_Score'].max()
    ]
})
fig2 = px.line_polar(radar_df, r='Selected Region', theta='Metric',␣
 ↪line_close=True, title="Region Profile vs Benchmark")
fig2.add_scatterpolar(r=radar_df['Max Value'], theta=radar_df['Metric'],␣
 ↪fill='none', name='Max Value')
st.plotly_chart(fig2, use_container_width=True)

# ---------- Strategic Summary ----------
st.markdown("###  Strategic Summary")
st.info("""
- **Region_32, Region_7, and Region_3** are top candidates for solar pilot␣
 ↪deployment based on high Solar Access Scores.
- These areas combine high irradiance, elevated energy cost, and limited grid␣
 ↪access.
- Next step: Validate on-ground logistics, community readiness, and policy␣
 ↪alignment.
""")
```

0.1.7 Strategic Summary

- **Region_32, Region_7, and Region_3** are top candidates for solar pilot deployment based on high Solar Access Scores.
- These areas combine high irradiance, elevated energy cost, and limited grid access.
- Next step: Validate on-ground logistics, community readiness, and policy alignment.

☀️ Prime Frontier Group – Solar Site Dashboard

📍 Metrics for Region_7

Solar Irradiance

7.08 kWh/m²/day

Grid Access

55.7%

Electricity Cost

$0.38 / kWh

Infrastructure Index

0.68

Terrain Ruggedness

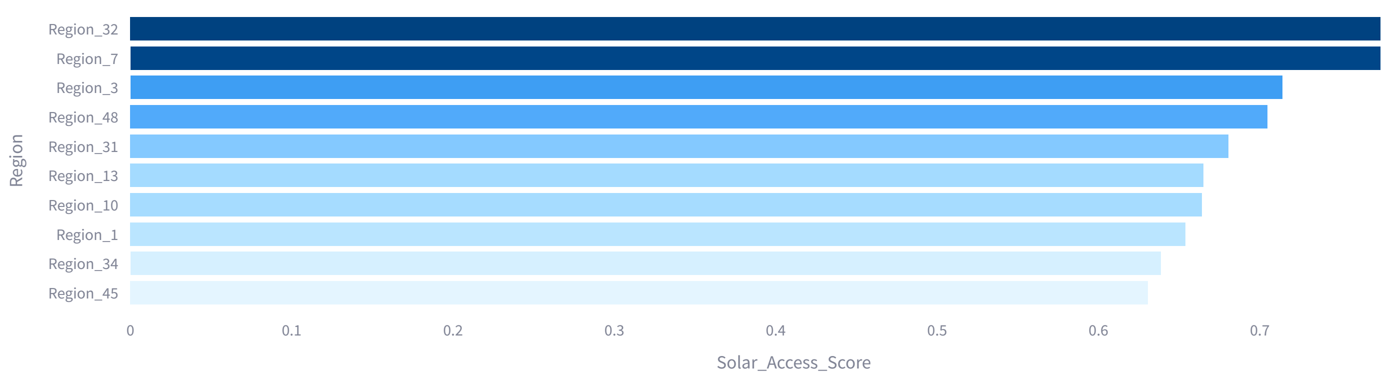
0.19

☀️ Solar Access Score

0.777

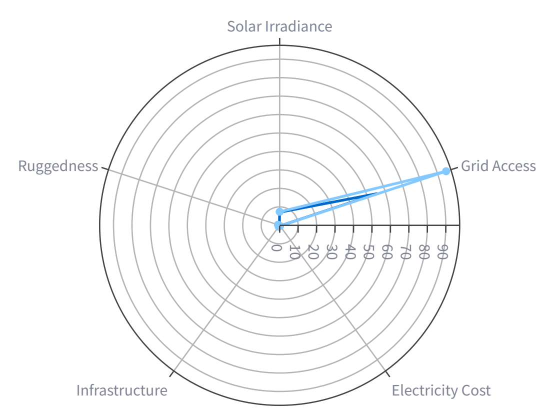
📊 Top 10 Regions by Solar Access Score

Top 10 Solar Suitability Rankings



🌐 Regional Profile vs Benchmark

Region Profile vs Benchmark



✅ Strategic Summary

- **Region_32, Region_7, and Region_3** are top candidates for solar pilot deployment based on high Solar Access Scores.

- These areas combine high irradiance, elevated energy cost, and limited grid access.
- Next step: Validate on-ground logistics, community readiness, and policy alignment.