District Sustainability Index (DSI) Prediction ☘️

End-to-End Machine Learning System | GCC Sustainability Innovation Lab

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This notebook presents a complete Machine Learning workflow to analyze sustainability indicators and predict the **District Sustainability Index (DSI)**.
It is designed to be clean, professional, and ready for GitHub & LinkedIn presentation.

Dataset: tm271data.csv

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Load Dataset & Basic Checks

Import Libraries

In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from IPython.display import HTML
import warnings
warnings.filterwarnings('ignore')
print("Libraries imported successfully ")
```

```
Libraries imported successfully
```

To have Custom CSS for Table and Text Formatting 😎

The following CSS enhances table visualization by centering text and improving the layout of DataFrame outputs.

In [2]:
```python
# Set display options
pd.set_option('display.max_colwidth', None)
pd.set_option('display.width', 2000)
pd.set_option('display.max_columns', None)
```

In [3]:
```python
from IPython.display import HTML

HTML("""
<style>
table.dataframe {
    border-collapse: collapse;
    width: 100%;
    table-layout: fixed;
}

/* header cells */
table.dataframe th {
    background-color: #cfe4ff;
    color: #003366;
    padding: 8px;
    border: 1px solid #aacbee;
    text-align: center !important;   /* CENTER TEXT */
    vertical-align: middle !important;
    font-weight: bold;
    word-wrap: break-word;
}

/* body cells */
table.dataframe td {
    padding: 8px;
    border: 1px solid #d5e6f5;
    text-align: center !important;   /* CENTER TEXT */
    vertical-align: middle !important;
    white-space: normal !important;
    word-wrap: break-word !important;
}


<style>
h1 {
    color: #1A2B4C !important;    /* Deep Navy */
    font-weight: 700 !important;
}

h2 {
    color: #D1495B !important;    /* Soft Coral Red */
    font-weight: 700 !important;
}
```

```
h3 {
    color: #127475 !important;    /* Elegant Teal */
    font-weight: 700 !important;
}

h4 {
    color: #CDA434 !important;    /* Warm Gold */
    font-weight: 700 !important;
}

h5 {
    color: #6D5BA8 !important;    /* Muted Lavender Purple */
    font-weight: 700 !important;
}
</style>


</style>
""")
```

Out[3]:

Part A : EDA

1-Load Dataset

In [4]:
```
df = pd.read_csv("tm271data.csv")
```

2-Data Exploration

In [5]:
```
#File Size Check
import os
file_size = os.path.getsize("tm271data.csv")
print(f"\nFile Size: {file_size:,} bytes ({file_size/1024:.2f} KB)")
```

```
File Size: 58,664 bytes (57.29 KB)
```

3-Basic Shape Info

In [6]:
```
print(f"Dataset Shape: {df.shape[0]} rows × {df.shape[1]} columns")
```

```
Dataset Shape: 1020 rows × 9 columns
```

4-Check Missing Columns (expected columns)

In [7]:
```
expected_columns = [
    'district_id', 'district_name', 'CO2_emission_kilotons',
    'Average_energy_consumption_kWh_per_household', 'Green_area_per_capita_m2',
    'Waste_recycling_rate_pct', 'Population_density_people_per_km2',
    'Traffic_index_0_100', 'DSI_target_0_100'
]

missing_cols = [col for col in expected_columns if col not in df.columns]
if missing_cols:
    print(f" Missing columns: {missing_cols}")
else:
    print(" All expected columns are present!")
```

```
All expected columns are present!
```

5-Check Duplicate Rows

In [8]:
```
duplicate_count = df.duplicated().sum()
print(f"\n Number of duplicate rows: {duplicate_count}")
if duplicate_count > 0:
    print(f"   → Removing {duplicate_count} duplicate rows...")
    df = df.drop_duplicates()
    print(f"   After removal: {df.shape[0]} rows")
```

```
Number of duplicate rows: 20
  → Removing 20 duplicate rows...
  After removal: 1000 rows
```

6-Missing Values Summary

In [9]:
```
total_missing = df.isnull().sum().sum()
print(f"Total missing values across dataset: {total_missing}")

total_cells = df.shape[0] * df.shape[1]
dirtiness_percentage = (total_missing / total_cells) * 100
print(f"Overall dirtiness percentage: {dirtiness_percentage:.2f}%")

missing_summary = df.isnull().sum().to_frame(name="Missing_Count")
```

```
missing_summary["Missing_%"] = (missing_summary["Missing_Count"] / len(df) * 100).round(2)

missing_summary
```

```
Total missing values across dataset: 486
Overall dirtiness percentage: 5.40%
```

Out[9]:

	Missing_Count	Missing_%
district_id	52	5.2
district_name	51	5.1
CO2_emission_kilotons	43	4.3
Average_energy_consumption_kWh_per_household	52	5.2
Green_area_per_capita_m2	60	6.0
Waste_recycling_rate_pct	54	5.4
Population_density_people_per_km2	53	5.3
Traffic_index_0_100	66	6.6
DSI_target_0_100	55	5.5

7-Shape info after removing Non-Predictive Columns

In [10]:
```
print("Shape:", df.shape)
```

```
Shape: (1000, 9)
```

In [11]:
```
df.head(5)
```

Out[11]:

	district_id	district_name	CO2_emission_kilotons	Average_energy_consumption_kWh_per_household	Green_area_per_capita_m2	Waste_recycling_rate_pct	Population_density_people_per_km2	Traffic_index_0_100	DSI_target_0_100
0	D524	District_524	1154.60	10771.2	6.85	32.3	1363.8	NaN	25.50
1	D603	District_603	286.76	NaN	32.78	36.7	143.0	NaN	65.37
2	D527	District_527	861.63	10140.8	16.31	20.4	1769.3	61.5	34.42
3	D032	District_032	287.53	7300.5	42.34	43.4	NaN	52.2	71.68
4	D617	District_617	83.49	6403.1	34.81	46.0	145.7	24.9	76.69

In [12]:
```
df.tail(5)
```

Out[12]:

	district_id	district_name	CO2_emission_kilotons	Average_energy_consumption_kWh_per_household	Green_area_per_capita_m2	Waste_recycling_rate_pct	Population_density_people_per_km2	Traffic_index_0_100	DSI_target_0_100
1015	D107	District_107	278.54	7677.2	41.86	44.7	88.1	41.1	73.03
1016	D271	District_271	640.15	8375.2	34.52	21.6	1960.1	46.9	53.71
1017	D861	District_861	1043.29	9210.5	15.70	42.2	1000.4	NaN	41.01
1018	D436	NaN	489.09	7547.0	24.86	44.8	154.0	45.3	62.93
1019	D103	District_103	531.45	8969.1	32.20	40.4	283.3	NaN	59.08

In [13]:
```
df.columns.tolist()
```

Out[13]:
```
['district_id',
 'district_name',
 'CO2_emission_kilotons',
 'Average_energy_consumption_kWh_per_household',
 'Green_area_per_capita_m2',
 'Waste_recycling_rate_pct',
 'Population_density_people_per_km2',
 'Traffic_index_0_100',
 'DSI_target_0_100']
```

In [14]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1000 entries, 0 to 1019
Data columns (total 9 columns):
 #   Column                                  Non-Null Count  Dtype  
---  ------                                  --------------  -----  
 0   district_id                             948 non-null    object 
 1   district_name                           949 non-null    object 
 2   CO2_emission_kilotons                   957 non-null    float64
 3   Average_energy_consumption_kWh_per_household  948 non-null    float64
 4   Green_area_per_capita_m2                940 non-null    float64
 5   Waste_recycling_rate_pct                946 non-null    float64
 6   Population_density_people_per_km2       947 non-null    float64
 7   Traffic_index_0_100                     934 non-null    float64
 8   DSI_target_0_100                        945 non-null    float64
dtypes: float64(7), object(2)
memory usage: 78.1+ KB
```

In [15]:
```
df.describe()
```

Out[15]:

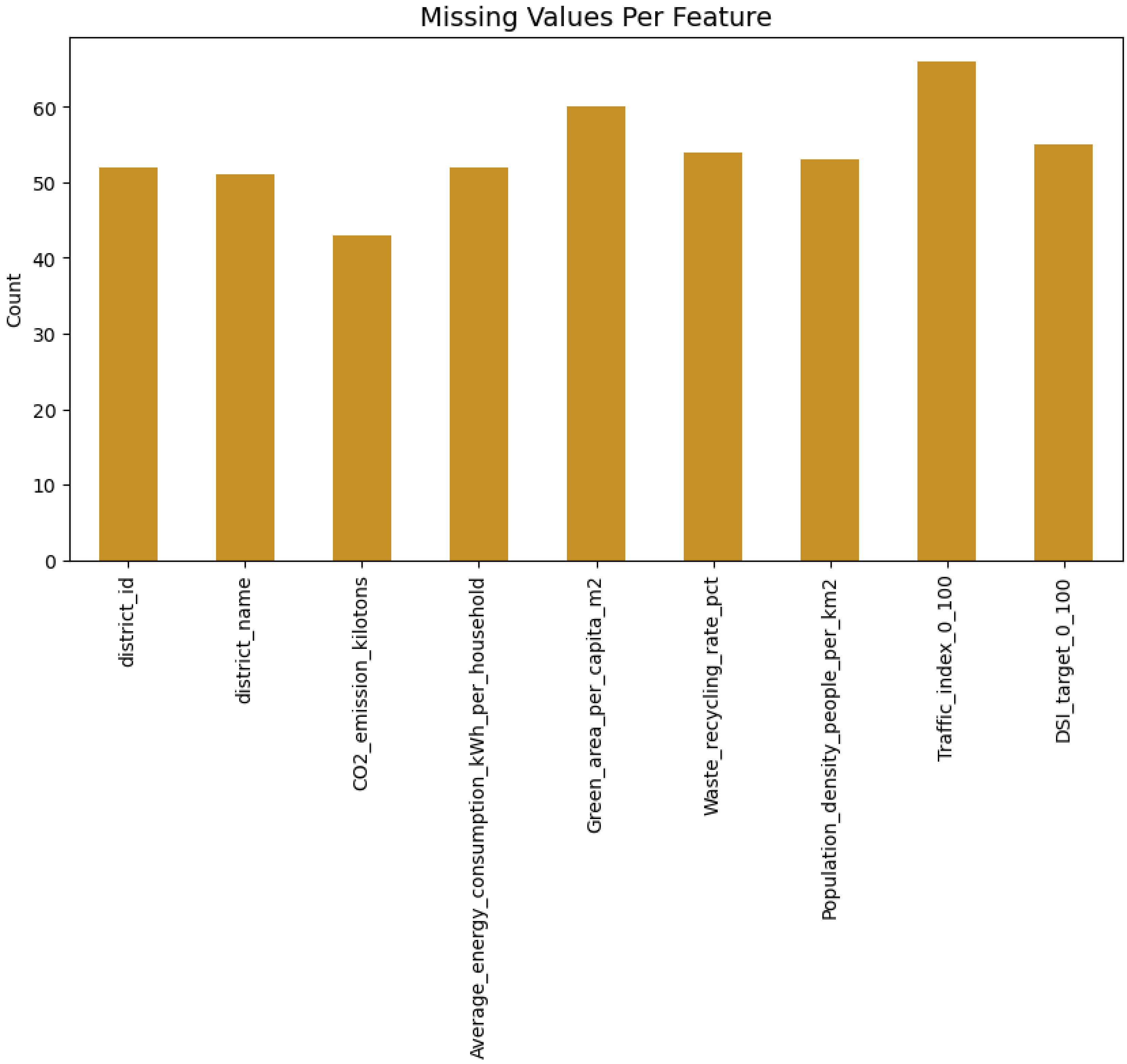
	CO2_emission_kilotons	Average_energy_consumption_kWh_per_household	Green_area_per_capita_m2	Waste_recycling_rate_pct	Population_density_people_per_km2	Traffic_index_0_100	DSI_target_0_100
count	957.000000	948.000000	940.000000	946.000000	947.000000	934.000000	945.000000
mean	629.987941	8567.462236	29.303043	39.731501	637.305913	55.356103	55.105153
std	258.511824	1435.045442	8.377738	9.080727	698.500321	19.904441	12.936851
min	20.000000	3809.500000	3.120000	6.100000	80.000000	5.000000	13.100000
25%	456.800000	7583.625000	23.505000	33.825000	227.350000	42.700000	46.930000
50%	626.870000	8548.000000	29.405000	39.800000	414.600000	55.200000	55.530000
75%	808.290000	9438.375000	34.810000	45.900000	763.600000	68.500000	63.740000
max	1440.280000	12894.800000	55.810000	68.700000	7511.400000	95.000000	92.590000

8-Data Visualizations:

Missing Values Per Feature :

This bar chart highlights how many missing entries appear in each feature.
It provides a clearer comparison than the heatmap and helps identify which variables require imputation.

In [16]:
```
missing = df.isnull().sum()
missing = missing[missing > 0]

plt.figure(figsize=(10,5))
missing.plot(kind="bar", color="#CB9428")
plt.title("Missing Values Per Feature", fontsize=14)
plt.ylabel("Count")
plt.show()
```

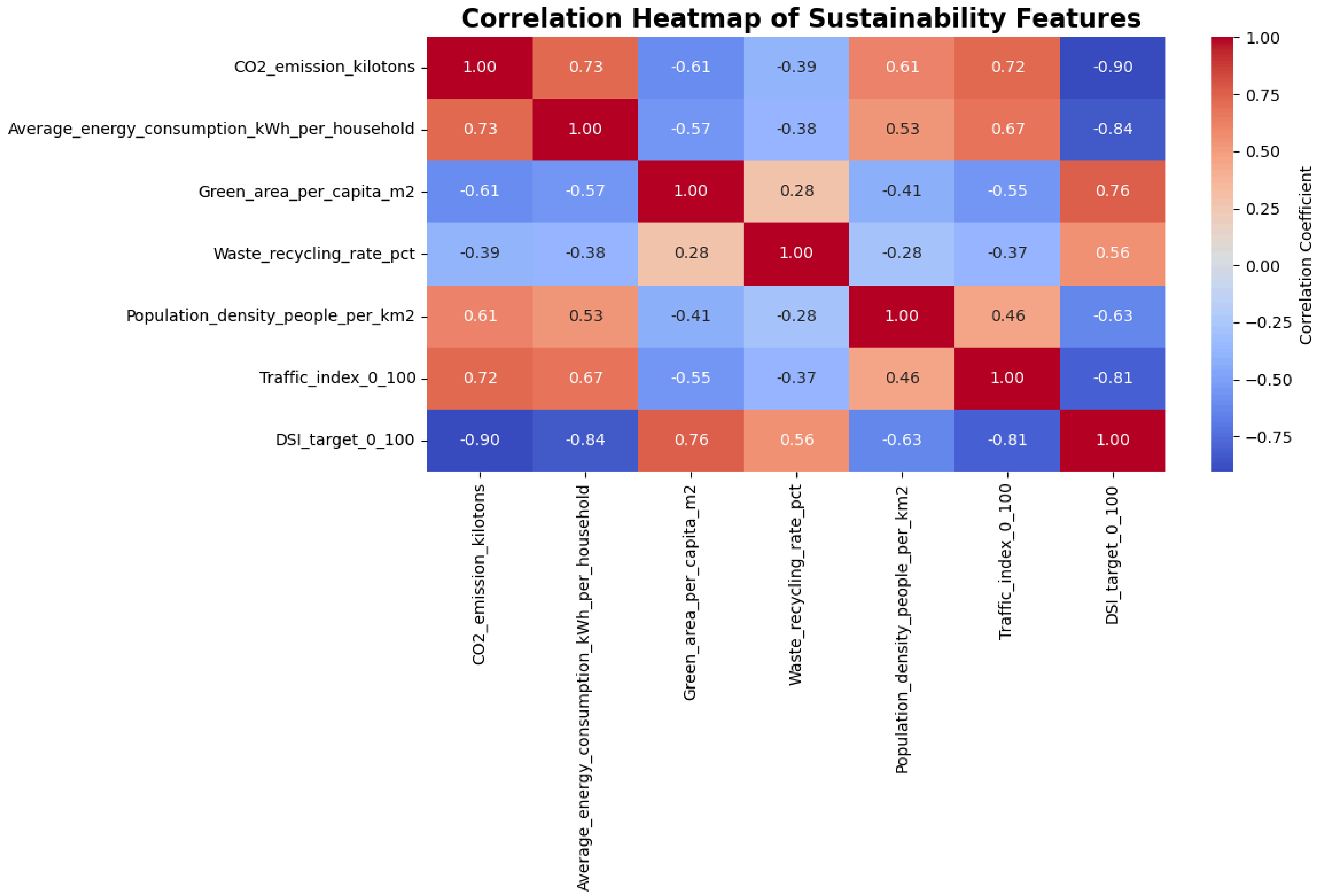


Correlation Heatmap of Sustainability Indicators :

The correlation heatmap visualizes the strength and direction of relationships between numerical features.

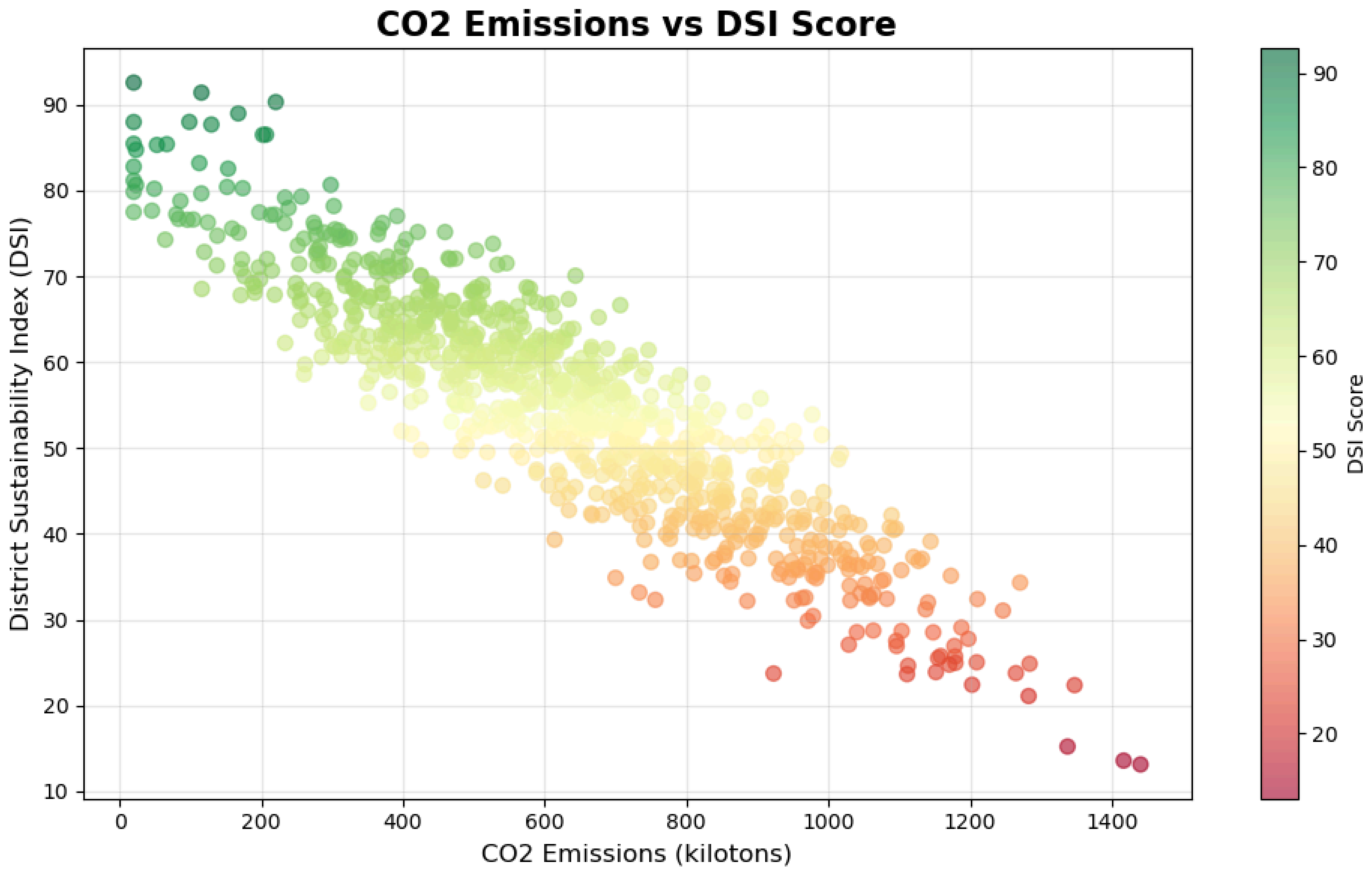
Positive correlations appear in red, while negative correlations appear in blue. This helps identify which sustainability factors are most strongly associated with the DSI score.

In [17]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap="coolwarm", fmt=".2f",
            cbar_kws={'label': 'Correlation Coefficient'})
plt.title(" Correlation Heatmap of Sustainability Features", fontsize=16, fontweight='bold')
plt.tight_layout()
plt.savefig('plot1_correlation_heatmap.png', dpi=300, bbox_inches='tight')
plt.show()
```



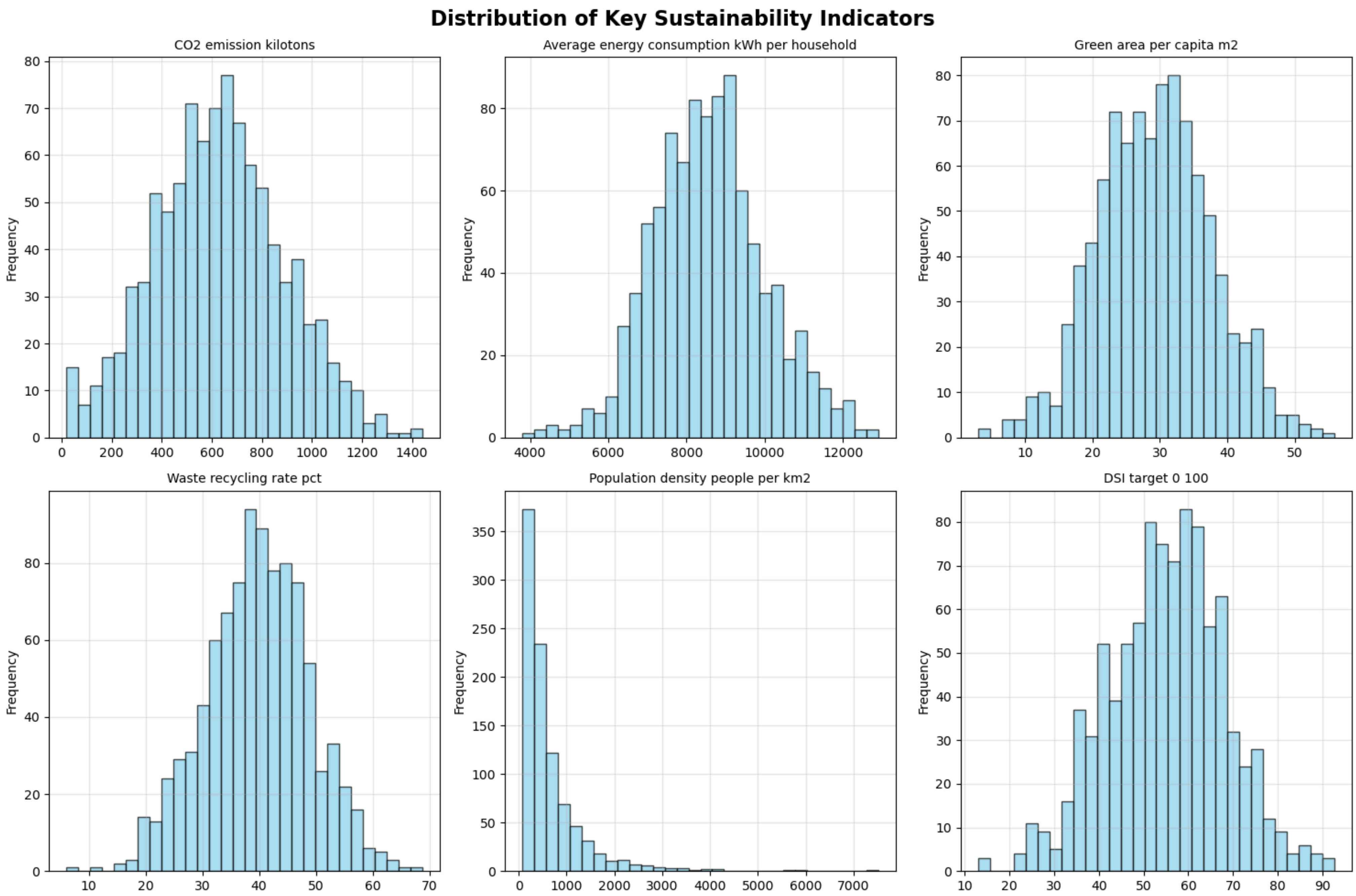
Scatter Plot - CO2 vs DSI

In [18]:
```
plt.figure(figsize=(10, 6))
plt.scatter(df['CO2_emission_kilotons'], df['DSI_target_0_100'],
            alpha=0.6, c=df['DSI_target_0_100'], cmap='RdYlGn', s=50)
plt.colorbar(label='DSI Score')
plt.xlabel('CO2 Emissions (kilotons)', fontsize=12)
plt.ylabel('District Sustainability Index (DSI)', fontsize=12)
plt.title('CO2 Emissions vs DSI Score', fontsize=16, fontweight='bold')
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.savefig('plot2_co2_vs_dsi.png', dpi=300, bbox_inches='tight')
plt.show()
```



Distribution Plots (Histograms) :

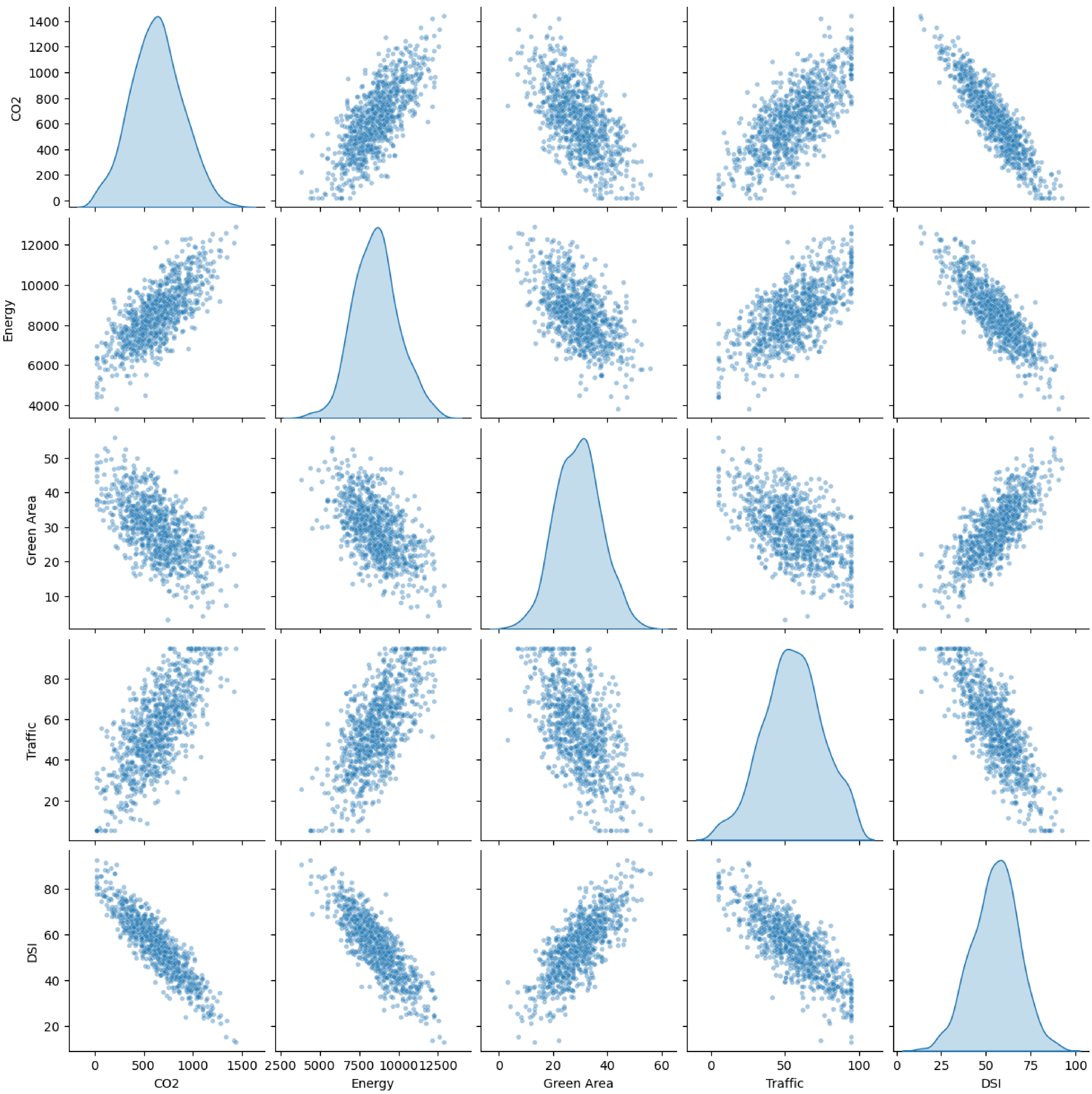
In [19]:
```python
fig, axes = plt.subplots(2, 3, figsize=(15, 10))
fig.suptitle(' Distribution of Key Sustainability Indicators',
             fontsize=16, fontweight='bold')

features_to_plot = [
    'CO2_emission_kilotons',
    'Average_energy_consumption_kWh_per_household',
    'Green_area_per_capita_m2',
    'Waste_recycling_rate_pct',
    'Population_density_people_per_km2',
    'DSI_target_0_100'
]

for idx, col in enumerate(features_to_plot):
    ax = axes[idx // 3, idx % 3]
    df[col].dropna().hist(bins=30, ax=ax, color='skyblue', edgecolor='black', alpha=0.7)
    ax.set_title(col.replace('_', ' '), fontsize=10)
    ax.set_ylabel('Frequency')
    ax.grid(True, alpha=0.3)

plt.tight_layout()
plt.savefig('plot3_distributions.png', dpi=300, bbox_inches='tight')
plt.show()
```



Pairplot :

In [20]:
```python
cols = [
    "CO2_emission_kilotons",
    "Average_energy_consumption_kWh_per_household",
    "Green_area_per_capita_m2",
    "Traffic_index_0_100",
    "DSI_target_0_100"
]

df_pair = df[cols].rename(columns={
    "CO2_emission_kilotons": "CO2",
    "Average_energy_consumption_kWh_per_household": "Energy",
    "Green_area_per_capita_m2": "Green Area",
    "Traffic_index_0_100": "Traffic",
    "DSI_target_0_100": "DSI"
})

g = sns.pairplot(df_pair, diag_kind="kde", plot_kws={"alpha": 0.4, "s": 15})
g.fig.suptitle("Pairplot of Key Sustainability Indicators",
               y=1.02, fontsize=16, fontweight='bold')
plt.savefig('plot4_pairplot.png', dpi=300, bbox_inches='tight')
plt.show()
```

Pairplot of Key Sustainability Indicators



THREE KEY OBSERVATIONS FROM EDA:

---

1 OBSERVATION 1: Strong Positive Correlation between CO_2 and Energy → Correlation coefficient: 0.732 → Interpretation: Districts with higher household energy consumption tend to have higher CO_2 emissions. This suggests energy efficiency improvements could directly reduce carbon footprint.

2 OBSERVATION 2: Green Area Shows Positive Impact on Sustainability → Correlation with DSI: 0.758 → Interpretation: Districts with more green space per capita tend to have higher sustainability scores. Investing in parks and green infrastructure can improve overall district sustainability.

3 OBSERVATION 3: Traffic Congestion Negatively Affects Sustainability → Correlation with DSI: -0.808 → Interpretation: Higher traffic index scores (more congestion) are associated with lower DSI scores. Improving public transportation could enhance sustainability outcomes.

Part B : Missing Values & Feature Engineering

1- Data Preprocessing

In this section, we clean and prepare the dataset for Machine Learning.
The preprocessing steps include handling missing values, encoding categorical variables, feature scaling, and preparing the final training dataset.

MISSING VALUE HANDLING

In [21]:
```
df.dtypes
```

Out[21]:
```
district_id                                object
district_name                              object
CO2_emission_kilotons                     float64
Average_energy_consumption_kWh_per_household    float64
Green_area_per_capita_m2                  float64
Waste_recycling_rate_pct                  float64
Population_density_people_per_km2         float64
Traffic_index_0_100                       float64
DSI_target_0_100                          float64
dtype: object
```

Removing Non-Predictive Columns: `district_id` and `district_name`

because they do not contribute to the predictive model. These fields are identifiers, not meaningful numerical features.

In [22]:
```
df_clean = df.drop(["district_id", "district_name"], axis=1)

# Store original variance for comparison
original_variance = df_clean.var()
print("\n Original Variance per Feature:")
print(original_variance)
```

```
 Original Variance per Feature:
CO2_emission_kilotons                          6.682836e+04
Average_energy_consumption_kWh_per_household   2.059355e+06
Green_area_per_capita_m2                       7.018650e+01
Waste_recycling_rate_pct                       8.245960e+01
Population_density_people_per_km2              4.879027e+05
Traffic_index_0_100                            3.961868e+02
DSI_target_0_100                               1.673621e+02
dtype: float64
```

In [23]:
```
df_clean.head(5)
```

Out[23]:

	CO2_emission_kilotons	Average_energy_consumption_kWh_per_household	Green_area_per_capita_m2	Waste_recycling_rate_pct	Population_density_people_per_km2	Traffic_index_0_100	DSI_target_0_100
0	1154.60	10771.2	6.85	32.3	1363.8	NaN	25.50
1	286.76	NaN	32.78	36.7	143.0	NaN	65.37
2	861.63	10140.8	16.31	20.4	1769.3	61.5	34.42
3	287.53	7300.5	42.34	43.4	NaN	52.2	71.68
4	83.49	6403.1	34.81	46.0	145.7	24.9	76.69

METHOD 1: Drop Rows with Missing Values

In [24]:
```
df_method1 = df_clean.dropna()
variance_method1 = df_method1.var()

print(f"Original shape: {df_clean.shape}")
print(f"After dropping: {df_method1.shape}")
print(f"Rows removed: {df_clean.shape[0] - df_method1.shape[0]}")
print(f"\nVariance after dropping:")
print(variance_method1)
```

```
Original shape: (1000, 7)
After dropping: (677, 7)
Rows removed: 323

Variance after dropping:
CO2_emission_kilotons                          6.870111e+04
Average_energy_consumption_kWh_per_household   2.115295e+06
Green_area_per_capita_m2                       6.973178e+01
Waste_recycling_rate_pct                       8.665239e+01
Population_density_people_per_km2              5.513975e+05
Traffic_index_0_100                            3.956760e+02
DSI_target_0_100                               1.748855e+02
dtype: float64
```

METHOD 2: Mean/Median Imputation

In [25]:
```
df_method2 = df_clean.fillna(df_clean.mean())
variance_method2 = df_method2.var()

print(f"Shape: {df_method2.shape}")
print(f"Missing values after imputation: {df_method2.isnull().sum().sum()}")
print(f"\nVariance after mean imputation:")
print(variance_method2)
```

```
Shape: (1000, 7)
Missing values after imputation: 0

Variance after mean imputation:
CO2_emission_kilotons                          6.395187e+04
Average_energy_consumption_kWh_per_household   1.952162e+06
Green_area_per_capita_m2                       6.597110e+01
Waste_recycling_rate_pct                       7.800232e+01
Population_density_people_per_km2              4.620180e+05
Traffic_index_0_100                            3.700123e+02
DSI_target_0_100                               1.581480e+02
dtype: float64
```

METHOD 3: Predictive Imputation (KNN Imputer)

In [26]:
```python
from sklearn.impute import KNNImputer

knn_imputer = KNNImputer(n_neighbors=5)
df_method3 = pd.DataFrame(
    knn_imputer.fit_transform(df_clean),
    columns=df_clean.columns
)
variance_method3 = df_method3.var()

print(f"Shape: {df_method3.shape}")
print(f"Missing values after KNN imputation: {df_method3.isnull().sum().sum()}")
print(f"\nVariance after KNN imputation:")
print(variance_method3)
```

```
Shape: (1000, 7)
Missing values after KNN imputation: 0

Variance after KNN imputation:
CO2_emission_kilotons                          6.484767e+04
Average_energy_consumption_kWh_per_household   1.986640e+06
Green_area_per_capita_m2                       6.806537e+01
Waste_recycling_rate_pct                       7.941579e+01
Population_density_people_per_km2              4.656203e+05
Traffic_index_0_100                            3.812641e+02
DSI_target_0_100                               1.631383e+02
dtype: float64
```

2- VARIANCE COMPARISON

In [27]:
```python
variance_comparison = pd.DataFrame({
    'Original': original_variance,
    'Method1_Drop': variance_method1,
    'Method2_Mean': variance_method2,
    'Method3_KNN': variance_method3
})

variance_comparison
```

Out[27]:

	Original	Method1_Drop	Method2_Mean	Method3_KNN
CO2_emission_kilotons	6.682836e+04	6.870111e+04	6.395187e+04	6.484767e+04
Average_energy_consumption_kWh_per_household	2.059355e+06	2.115295e+06	1.952162e+06	1.986640e+06
Green_area_per_capita_m2	7.018650e+01	6.973178e+01	6.597110e+01	6.806537e+01
Waste_recycling_rate_pct	8.245960e+01	8.665239e+01	7.800232e+01	7.941579e+01
Population_density_people_per_km2	4.879027e+05	5.513975e+05	4.620180e+05	4.656203e+05
Traffic_index_0_100	3.961868e+02	3.956760e+02	3.700123e+02	3.812641e+02
DSI_target_0_100	1.673621e+02	1.748855e+02	1.581480e+02	1.631383e+02

In [28]:
```python
# Variance change percentage
variance_change = pd.DataFrame({
    'Method1_Drop_%': ((variance_method1 - original_variance) / original_variance * 100),
    'Method2_Mean_%': ((variance_method2 - original_variance) / original_variance * 100),
    'Method3_KNN_%': ((variance_method3 - original_variance) / original_variance * 100)
})

print("\n Variance Change (%) from Original:-")
variance_change
```

```
 Variance Change (%) from Original:-
```

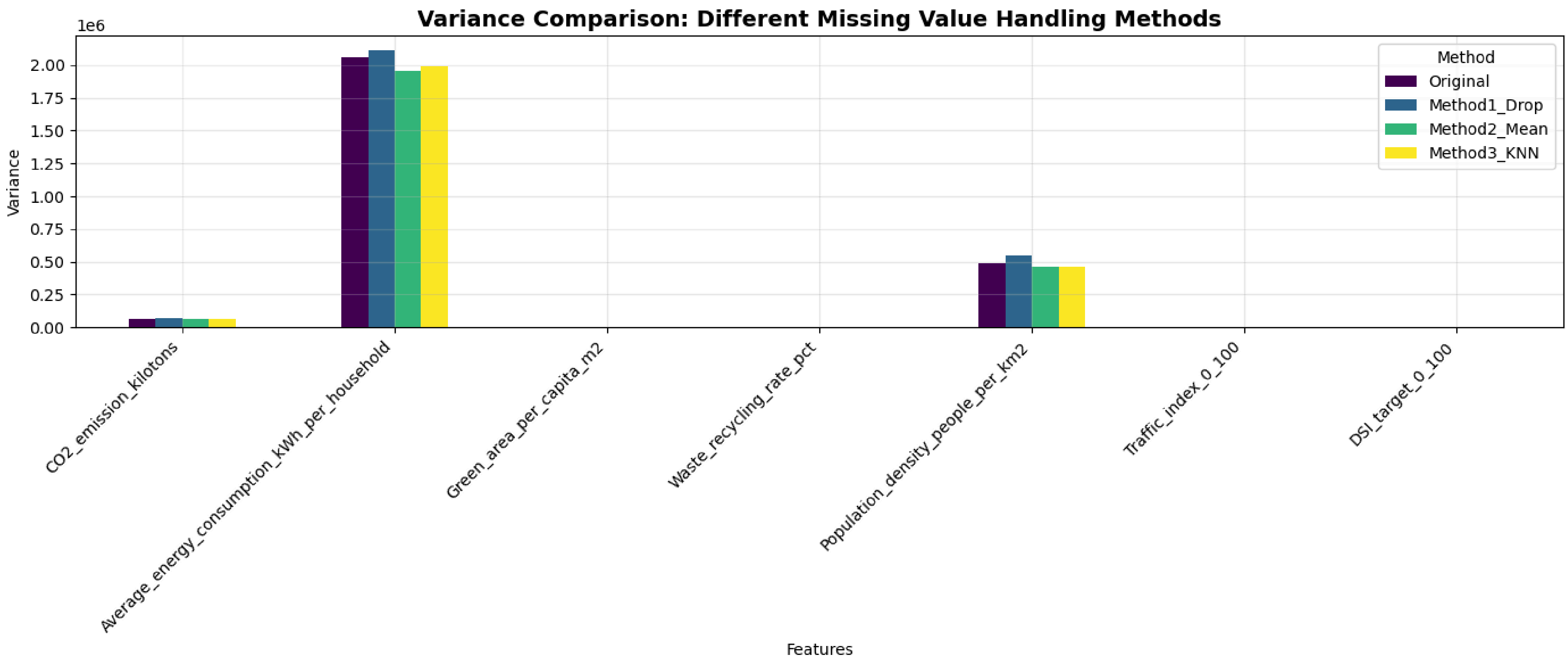
Out[28]:

	Method1_Drop_%	Method2_Mean_%	Method3_KNN_%
CO2_emission_kilotons	2.802316	-4.304304	-2.963853
Average_energy_consumption_kWh_per_household	2.716342	-5.205205	-3.530984
Green_area_per_capita_m2	-0.647872	-6.006006	-3.022138
Waste_recycling_rate_pct	5.084656	-5.405405	-3.691272
Population_density_people_per_km2	13.013829	-5.305305	-4.566985
Traffic_index_0_100	-0.128917	-6.606607	-3.766566
DSI_target_0_100	4.495300	-5.505506	-2.523752

3- Visualization

In [29]:
```
plt.figure(figsize=(14, 6))
variance_comparison.plot(kind='bar', figsize=(14, 6), colormap='viridis')
plt.title('Variance Comparison: Different Missing Value Handling Methods',
          fontsize=14, fontweight='bold')
plt.xlabel('Features')
plt.ylabel('Variance')
plt.xticks(rotation=45, ha='right')
plt.legend(title='Method')
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.savefig('variance_comparison.png', dpi=300, bbox_inches='tight')
plt.show()
```

```
<Figure size 1400x600 with 0 Axes>
```



Conclusion: KNN Imputation preserves variance best while retaining all data!

In [30]:
```
# Use Method 2 (Mean Imputation) for rest of analysis
df_clean = df_method2.copy()
```

4- FEATURE TRANSFORMATION

DERIVED FEATURE 1: Energy per Capita

In [31]:
```
print("\n Creating Derived Feature 1: Energy per Capita")

df_clean['Energy_per_capita'] = (
    df_clean['Average_energy_consumption_kWh_per_household'] /
    (df_clean['Population_density_people_per_km2'])
)

print("Energy_per_capita = Energy_consumption / Population_density")
print(f"   → Mean: {df_clean['Energy_per_capita'].mean():.2f}")
print(f"   → Std: {df_clean['Energy_per_capita'].std():.2f}")
```

```
 Creating Derived Feature 1: Energy per Capita
Energy_per_capita = Energy_consumption / Population_density
   → Mean: 26.06
   → Std: 20.65
```

WHY THIS IMPROVES INTERPRETABILITY:

This feature normalizes energy consumption by population, revealing which districts are energy-intensive per person, not just per household. It helps identify inefficient areas regardless of population size.

DERIVED FEATURE 2: Green Index

In [32]:
```
df_clean['Green_Index'] = (
    df_clean['Green_area_per_capita_m2'] /
    (df_clean['Population_density_people_per_km2'])
)

print("Green_Index = Green_area_per_capita / Population_density")
print(f"   → Mean: {df_clean['Green_Index'].mean():.4f}")
print(f"   → Std: {df_clean['Green_Index'].std():.4f}")
```

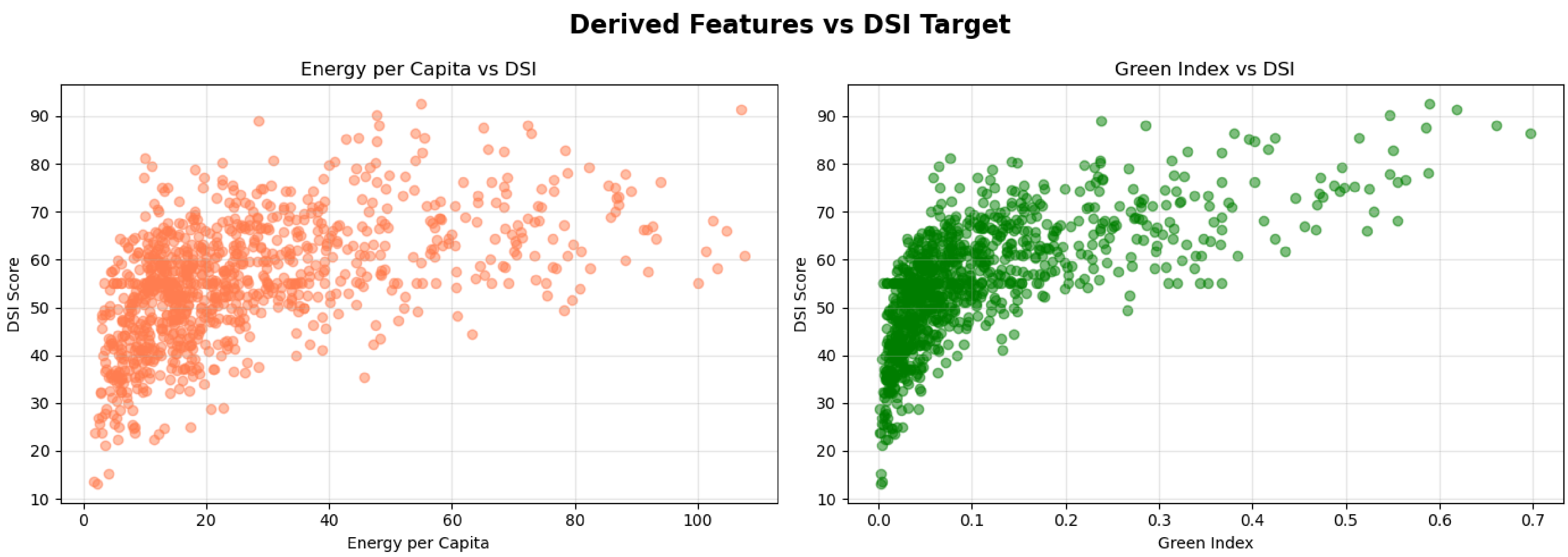
```
Green_Index = Green_area_per_capita / Population_density
   → Mean: 0.1063
   → Std: 0.1133
```

WHY THIS IMPROVES INTERPRETABILITY ??

This feature shows the availability of green space relative to crowding. Dense urban areas might have green space, but if overcrowded, the benefit per person is reduced. This metric captures true green space accessibility.

5- Visualize new features vs DSI

In [33]:
```
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

axes[0].scatter(df_clean['Energy_per_capita'], df_clean['DSI_target_0_100'],
                alpha=0.5, c='coral')
axes[0].set_xlabel('Energy per Capita')
axes[0].set_ylabel('DSI Score')
axes[0].set_title('Energy per Capita vs DSI')
axes[0].grid(True, alpha=0.3)

axes[1].scatter(df_clean['Green_Index'], df_clean['DSI_target_0_100'],
                alpha=0.5, c='green')
axes[1].set_xlabel('Green Index')
axes[1].set_ylabel('DSI Score')
axes[1].set_title('Green Index vs DSI')
axes[1].grid(True, alpha=0.3)

plt.suptitle(' Derived Features vs DSI Target', fontsize=16, fontweight='bold')
plt.tight_layout()
plt.savefig('derived_features_vs_dsi.png', dpi=300, bbox_inches='tight')
plt.show()

print("\n Two derived features created successfully!")
```




```
Two derived features created successfully!
```

6- FEATURE SCALING & DIMENSIONALITY REDUCTION

Prepare features and target

In [34]:
```
X = df_clean.drop("DSI_target_0_100", axis=1)
y = df_clean["DSI_target_0_100"]

print(f"\n Features shape: {X.shape}")
print(f" Target shape: {y.shape}")
```

```
Features shape: (1000, 8)
Target shape: (1000,)
```

SCALING METHOD 1: Min-Max Scaling

In [35]:
```python
from sklearn.preprocessing import MinMaxScaler

minmax_scaler = MinMaxScaler()
X_minmax = minmax_scaler.fit_transform(X)
X_minmax_df = pd.DataFrame(X_minmax, columns=X.columns)

print(" Min-Max Scaling applied!")
print(f"   → All features now scaled to range [0, 1]")
print(f"\nSample of scaled data:")
X_minmax_df.head()
```

```
Min-Max Scaling applied!
  → All features now scaled to range [0, 1]

Sample of scaled data:
```

Out[35]:

	CO2_emission_kilotons	Average_energy_consumption_kWh_per_household	Green_area_per_capita_m2	Waste_recycling_rate_pct	Population_density_people_per_km2	Traffic_index_0_100	Energy_per_capita	Green_Index
0	0.798857	0.766260	0.070791	0.418530	0.172753	0.559512	0.059318	0.005311
1	0.187822	0.523699	0.562915	0.488818	0.008478	0.559512	0.550175	0.327310
2	0.592580	0.696873	0.250332	0.228435	0.227319	0.627778	0.038874	0.011337
3	0.188364	0.384247	0.744354	0.595847	0.074993	0.524444	0.092888	0.093510
4	0.044702	0.285472	0.601442	0.637380	0.008841	0.221111	0.399512	0.341219

Handling Missing Values

Since all remaining features are numerical, we applied mean imputation to replace missing values.
This preserves the overall distribution of the data without removing any records.

SCALING METHOD 2: Standardization (Z-score)

In [36]:
```python
from sklearn.preprocessing import StandardScaler
standard_scaler = StandardScaler()
X_standard = standard_scaler.fit_transform(X)
X_standard_df = pd.DataFrame(X_standard, columns=X.columns)

print(" Standardization applied!")
print(f" All features now have mean=0 and std=1")
print(f"\nSample of standardized data:")
X_standard_df.head()
```

```
Standardization applied!
All features now have mean=0 and std=1

Sample of standardized data:
```

Out[36]:

	CO2_emission_kilotons	Average_energy_consumption_kWh_per_household	Green_area_per_capita_m2	Waste_recycling_rate_pct	Population_density_people_per_km2	Traffic_index_0_100	Energy_per_capita	Green_Index
0	2.075530	1.578045	-2.765767	-0.841860	1.069350	3.695723e-16	-0.880080	-0.893982
1	-1.357917	0.000000	0.428292	-0.343417	-0.727585	3.695723e-16	1.640406	1.085247
2	0.916448	1.126630	-1.600484	-2.189924	1.666219	3.195605e-01	-0.985058	-0.856945
3	-1.354871	-0.907242	1.605893	0.415577	0.000000	-1.641573e-01	-0.707701	-0.351848
4	-2.162117	-1.549849	0.678347	0.710112	-0.723611	-1.584103e+00	0.866774	1.170741

7- DIMENSIONALITY REDUCTION: PCA

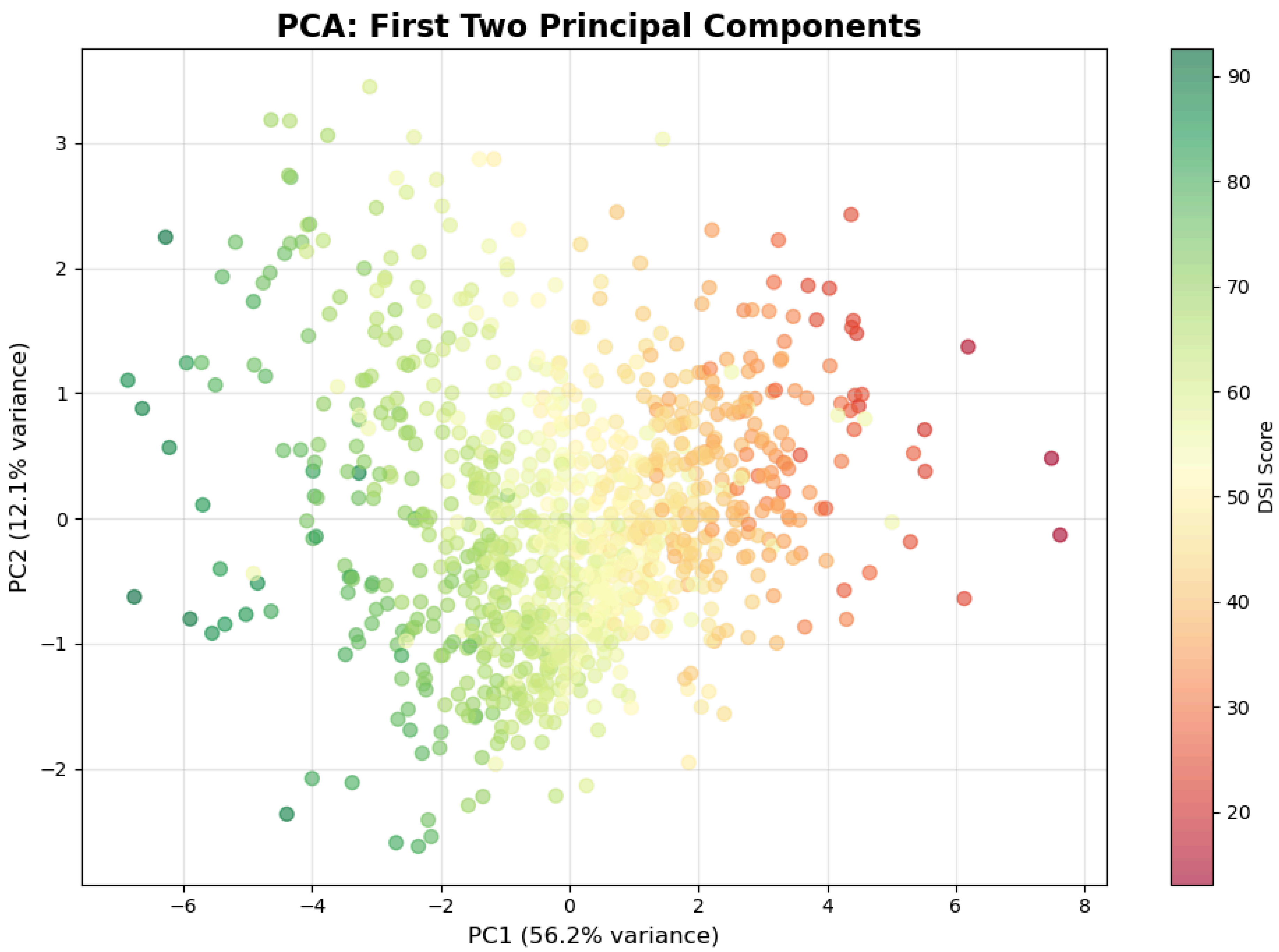
In [37]:
```python
from sklearn.decomposition import PCA
pca = PCA(n_components=2)  # Apply PCA to reduce to 2 components
X_pca = pca.fit_transform(X_standard)
print(f"\n Explained Variance Ratio:")
print(f"   → PC1: {pca.explained_variance_ratio_[0]:.4f} ({pca.explained_variance_ratio_[0]*100:.2f}%)")
print(f"   → PC2: {pca.explained_variance_ratio_[1]:.4f} ({pca.explained_variance_ratio_[1]*100:.2f}%)")
print(f"   → Total variance explained: {pca.explained_variance_ratio_.sum()*100:.2f}%")
```

```
Explained Variance Ratio:
  → PC1: 0.5617 (56.17%)
  → PC2: 0.1213 (12.13%)
  → Total variance explained: 68.31%
```

8- Visualize PCA components

In [38]:
```python
plt.figure(figsize=(10, 7))
scatter = plt.scatter(X_pca[:, 0], X_pca[:, 1],
                     c=y, cmap='RdYlGn', alpha=0.6, s=50)
```

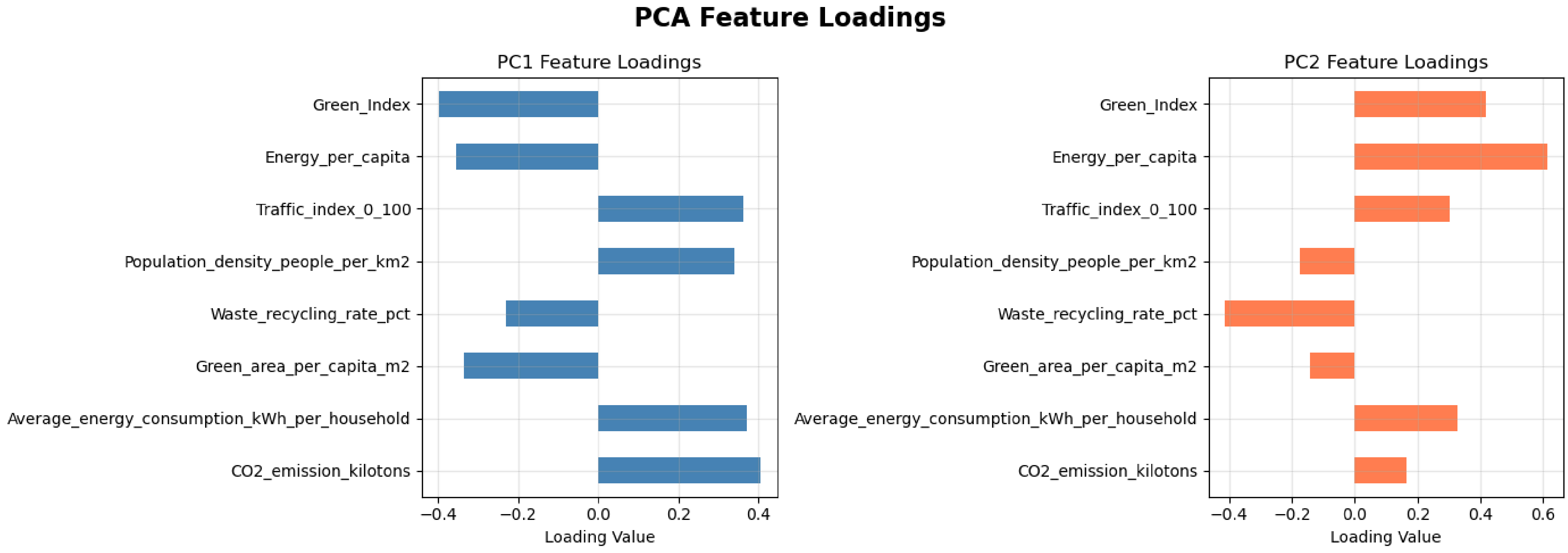
```python
plt.colorbar(scatter, label='DSI Score')
plt.xlabel(f'PC1 ({pca.explained_variance_ratio_[0]*100:.1f}% variance)', fontsize=12)
plt.ylabel(f'PC2 ({pca.explained_variance_ratio_[1]*100:.1f}% variance)', fontsize=12)
plt.title(' PCA: First Two Principal Components', fontsize=16, fontweight='bold')
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.savefig('pca_visualization.png', dpi=300, bbox_inches='tight')
plt.show()
```



In [39]:
```python
loadings = pd.DataFrame(
    pca.components_.T,
    columns=['PC1', 'PC2'],
    index=X.columns
)

print("\n PCA Component Loadings (Feature Contributions):")
print(loadings)
```

```
 PCA Component Loadings (Feature Contributions):
                                            PC1       PC2
CO2_emission_kilotons                   0.405931  0.166006
Average_energy_consumption_kWh_per_household  0.371364  0.329392
Green_area_per_capita_m2               -0.335458 -0.142486
Waste_recycling_rate_pct               -0.231623 -0.413712
Population_density_people_per_km2       0.338941 -0.176507
Traffic_index_0_100                     0.363156  0.302576
Energy_per_capita                      -0.353906  0.612777
Green_Index                            -0.398892  0.417470
```

In [40]:
```python
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

loadings['PC1'].plot(kind='barh', ax=axes[0], color='steelblue')
axes[0].set_title('PC1 Feature Loadings')
axes[0].set_xlabel('Loading Value')
axes[0].grid(True, alpha=0.3)
loadings['PC2'].plot(kind='barh', ax=axes[1], color='coral')
axes[1].set_title('PC2 Feature Loadings')
axes[1].set_xlabel('Loading Value')
axes[1].grid(True, alpha=0.3)

plt.suptitle(' PCA Feature Loadings', fontsize=16, fontweight='bold')
plt.tight_layout()
plt.savefig('pca_loadings.png', dpi=300, bbox_inches='tight')
plt.show()
```



Part C : Modeling

1- Choose the Regression Model

Why a Regression Model?

The target variable **DSI_target_0_100** contains continuous numerical values ranging from 0 to 100. Therefore, the goal is to predict a numerical score, not to classify districts into predefined categories. For this reason, a regression approach is the correct and scientifically appropriate choice for this dataset.

2- Train/Test Split data:

In [41]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X_standard, y, test_size=0.2, random_state=42
)

print(f"\n Training set: {X_train.shape}")
print(f" Test set: {X_test.shape}")
```

```
Training set: (800, 8)
Test set: (200, 8)
```

3- Model Training

In this section, we train multiple Machine Learning models to predict the District Sustainability Index (DSI).
We apply different algorithms and later compare their performance using common regression metrics:

- MAE (Mean Absolute Error)
- RMSE (Root Mean Squared Error)
- R^2 Score (Coefficient of Determination)

Import models

In [42]:
```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

Train models

In this step, I extended the base models by adding ensemble learning methods to improve prediction performance.
I used two ensemble techniques:

- **Random Forest Regressor (Bagging)**
- **Gradient Boosting Regressor (Boosting)**

These models were trained using the same train/test split, and their performance was compared to the base models.
Ensemble methods generally provide better accuracy because they combine multiple learners and reduce overfitting.

In [43]:
```
models = {
    "Linear Regression": LinearRegression(),
    "Decision Tree": DecisionTreeRegressor(
    random_state=42,
```

```
        max_depth=8,
        min_samples_split=40,
        min_samples_leaf=20,
        max_features='sqrt',
        ccp_alpha=0.02
        ),

        "Support Vector Regressor": SVR(kernel="rbf"),

        "Random Forest": RandomForestRegressor(
            random_state=42,
            n_estimators=200,
            max_depth=15,
            min_samples_split=20,
            min_samples_leaf=10,
            max_features='sqrt'
        ),
        "Gradient Boosting": GradientBoostingRegressor(
        random_state=42,
        n_estimators=100,
        learning_rate=0.1,
        max_depth=4,
        min_samples_split=20,
        min_samples_leaf=10,
        subsample=0.8,
        max_features='sqrt'
    )
    }
```

In [44]:

```
# Train and evaluate
results = []

for name, model in models.items():
    print(f"\n🔄 Training {name}...")
    model.fit(X_train, y_train)

    preds = model.predict(X_test)
    mae = mean_absolute_error(y_test, preds)
    rmse = np.sqrt(mean_squared_error(y_test, preds))
    r2 = r2_score(y_test, preds)

    results.append([name, mae, rmse, r2])
    print(f"   MAE: {mae:.4f}, RMSE: {rmse:.4f}, R²: {r2:.4f}")
```

```
🔄 Training Linear Regression...
   MAE: 2.7660, RMSE: 4.6316, R²: 0.8712

🔄 Training Decision Tree...
   MAE: 5.1917, RMSE: 6.9041, R²: 0.7138

🔄 Training Support Vector Regressor...
   MAE: 3.7786, RMSE: 5.8325, R²: 0.7957

🔄 Training Random Forest...
   MAE: 3.4491, RMSE: 4.8717, R²: 0.8575

🔄 Training Gradient Boosting...
   MAE: 3.0975, RMSE: 4.6857, R²: 0.8682
```

Results table

In [45]:

```
results_df = pd.DataFrame(results, columns=["Model", "MAE", "RMSE", "R² Score"])
print(" MODEL EVALUATION RESULTS:")
results_df
```

```
MODEL EVALUATION RESULTS:
```

Out[45]:

	Model	MAE	RMSE	R^2 Score
0	Linear Regression	2.766036	4.631590	0.871182
1	Decision Tree	5.191736	6.904054	0.713763
2	Support Vector Regressor	3.778582	5.832480	0.795721
3	Random Forest	3.449102	4.871703	0.857479
4	Gradient Boosting	3.097549	4.685676	0.868156

4- which one is the Best model ?

In [46]:

```
best_row = results_df.loc[results_df["RMSE"].idxmin()]
best_model_name = best_row["Model"]
best_model = models[best_model_name]

print(f"\n🏆 BEST MODEL: {best_model_name}")
print(f"   → MAE: {best_row['MAE']:.4f}")
print(f"   → RMSE: {best_row['RMSE']:.4f}")
print(f"   → R²: {best_row['R² Score']:.4f}")
```

```
🏆 BEST MODEL: Linear Regression
  → MAE: 2.7660
  → RMSE: 4.6316
  → R²: 0.8712
```

- Alternative Improved Selection Method (Ranking Approach) :-

To avoid relying on RMSE alone, a ranking method is added to compare models across MAE, RMSE, and R^2 together.
This gives a more balanced evaluation.
Both methods chose the same best model, which confirms the result.

In [47]:
```python
# Create ranking for each metric
results_df["MAE_rank"] = results_df["MAE"].rank(ascending=True)
results_df["RMSE_rank"] = results_df["RMSE"].rank(ascending=True)
results_df["R2_rank"] = results_df["R² Score"].rank(ascending=False)

results_df["Average_Rank"] = (results_df["MAE_rank"] +
                              results_df["RMSE_rank"] +
                              results_df["R2_rank"]) / 3

# Best model = lowest average rank
best_model_row = results_df.loc[results_df["Average_Rank"].idxmin()]
best_model_name = best_model_row["Model"]

best_model_name, best_model_row
```

Out[47]:
```
('Linear Regression',
 Model           Linear Regression
 MAE                      2.766036
 RMSE                      4.63159
 R² Score                 0.871182
 MAE_rank                      1.0
 RMSE_rank                     1.0
 R2_rank                       1.0
 Average_Rank                  1.0
 Name: 0, dtype: object)
```

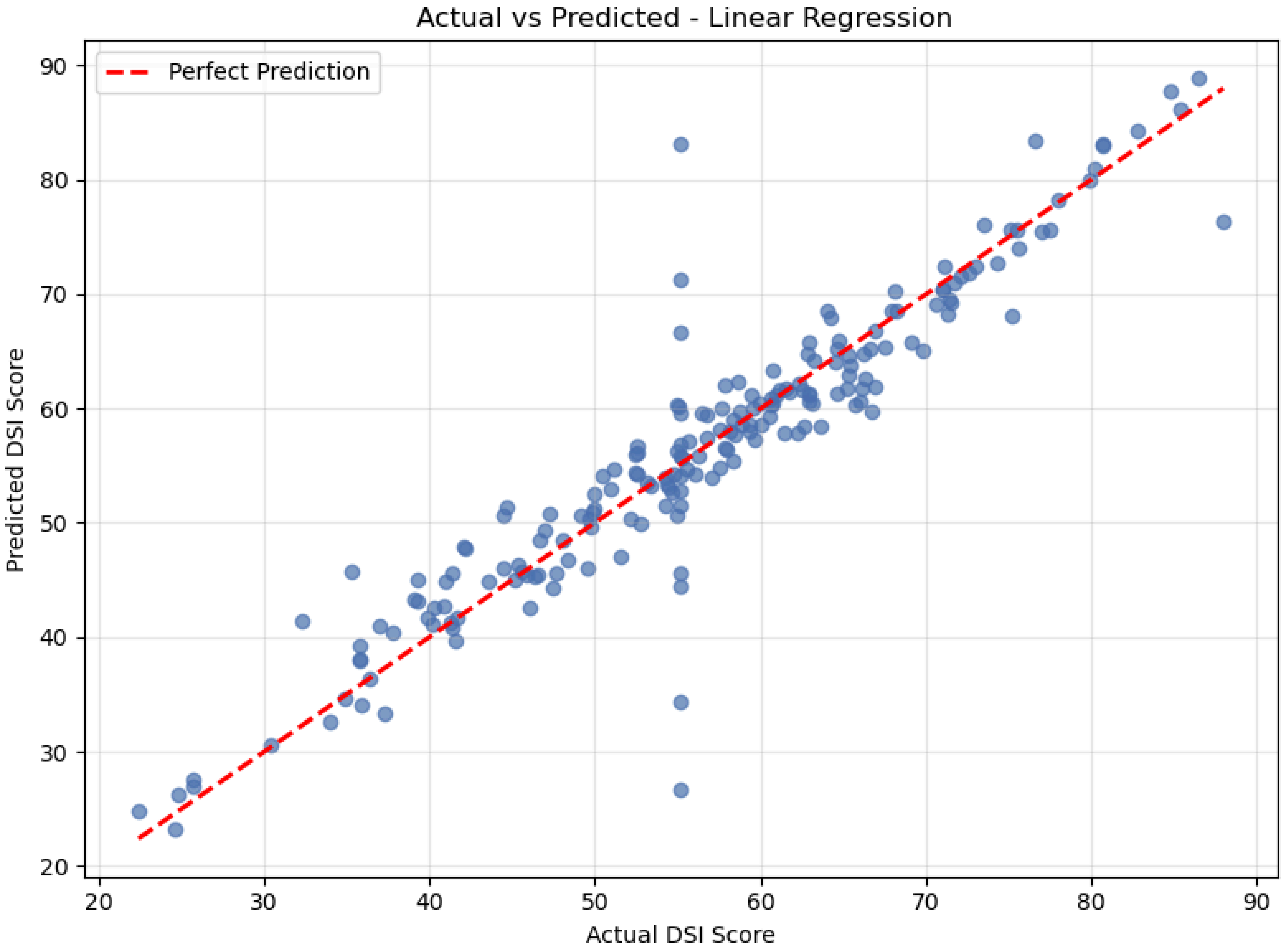
5- Feature importance

In [48]:
```python
if hasattr(best_model, 'feature_importances_'):
    importances = best_model.feature_importances_
    feature_importance_df = pd.DataFrame({
        'Feature': X.columns,
        'Importance': importances
    }).sort_values('Importance', ascending=False)

    plt.figure(figsize=(10, 6))
    plt.barh(feature_importance_df['Feature'], feature_importance_df['Importance'], color='steelblue')
    plt.xlabel('Importance Score')
    plt.title(f' Feature Importance - {best_model_name}', fontsize=14, fontweight='bold')
    plt.gca().invert_yaxis()
    plt.tight_layout()
    plt.savefig('feature_importance.png', dpi=300, bbox_inches='tight')
    plt.show()
```

6- Visualizations

Actual vs Predicted

In [49]:
```python
final_predictions = best_model.predict(X_test)

# Actual vs Predicted
plt.figure(figsize=(8, 6))
plt.scatter(y_test, final_predictions, alpha=0.7, color='#4c72b0')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()],
         'r--', lw=2, label='Perfect Prediction')
plt.xlabel('Actual DSI Score')
plt.ylabel('Predicted DSI Score')
plt.title(f' Actual vs Predicted - {best_model_name}')
plt.legend()
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.savefig('actual_vs_predicted.png', dpi=300, bbox_inches='tight')
plt.show()
```



NOTE: Why Some Points Appear Vertically Aligned ?

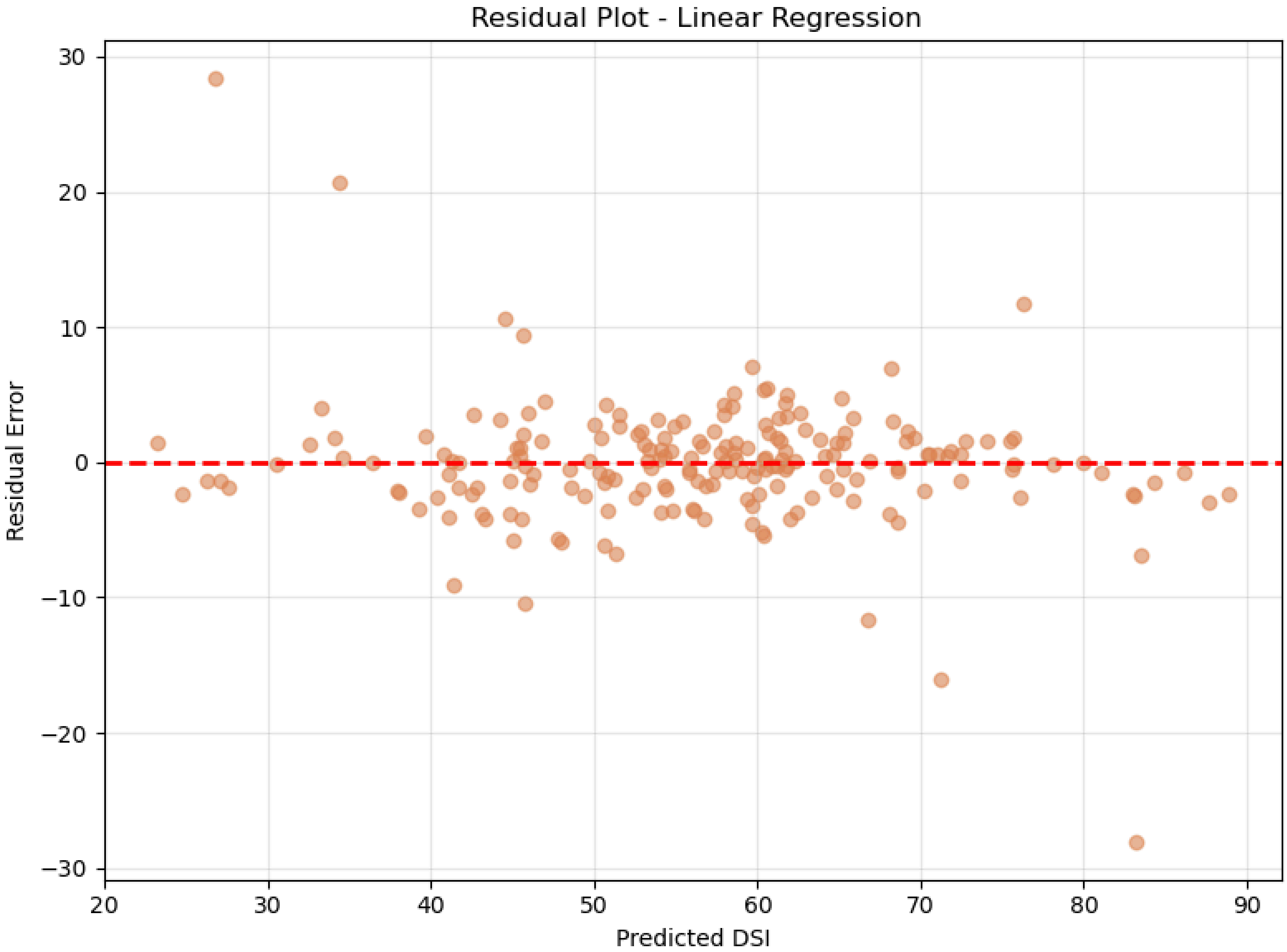
In the scatter plot, some points appear vertically aligned (stacked above each other).This is completely normal in regression visualizations.

The reason is that several data samples share the **same actual value** on the x-axis, but the model predicts **different values** for them on the y-axis.So when multiple rows have the same Actual DSI Score, all their predicted values stack vertically.

This does **not** indicate any issue in the model or the plot. It simply reflects that the dataset contains repeated actual values, which is very common in regression tasks.

Residual plot

In [50]:
```
residuals = y_test - final_predictions
plt.figure(figsize=(8, 6))
plt.scatter(final_predictions, residuals, alpha=0.6, color='#dd8452')
plt.axhline(0, color='red', linestyle='--', lw=2)
plt.xlabel('Predicted DSI')
plt.ylabel('Residual Error')
plt.title(f' Residual Plot - {best_model_name}')
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.savefig('residual_plot.png', dpi=300, bbox_inches='tight')
plt.show()
```



7- !Over/Underfitting Analysis!

In [51]:
```
for name, model in models.items():
    # Train predictions
    train_preds = model.predict(X_train)
    train_r2 = r2_score(y_train, train_preds)
    train_rmse = np.sqrt(mean_squared_error(y_train, train_preds))

    # Test predictions
    test_preds = model.predict(X_test)
    test_r2 = r2_score(y_test, test_preds)
    test_rmse = np.sqrt(mean_squared_error(y_test, test_preds))

    # Calculate gap
    r2_gap = train_r2 - test_r2
    rmse_gap = test_rmse - train_rmse

    # Diagnosis rules
    if r2_gap > 0.20:
        diagnosis = "⚠ OVERFITTING"
    elif r2_gap < 0.05:
        diagnosis = "🔥 PERFECT GENERALIZATION"
    else:
        diagnosis = "✅ GOOD FIT"

    print(f"\n{name}:")
    print(f"   Train R²: {train_r2:.4f} | Test R²: {test_r2:.4f} | Gap: {r2_gap:.4f}")
    print(f"   Train RMSE: {train_rmse:.4f} | Test RMSE: {test_rmse:.4f}")
    print(f"   {diagnosis}")
```

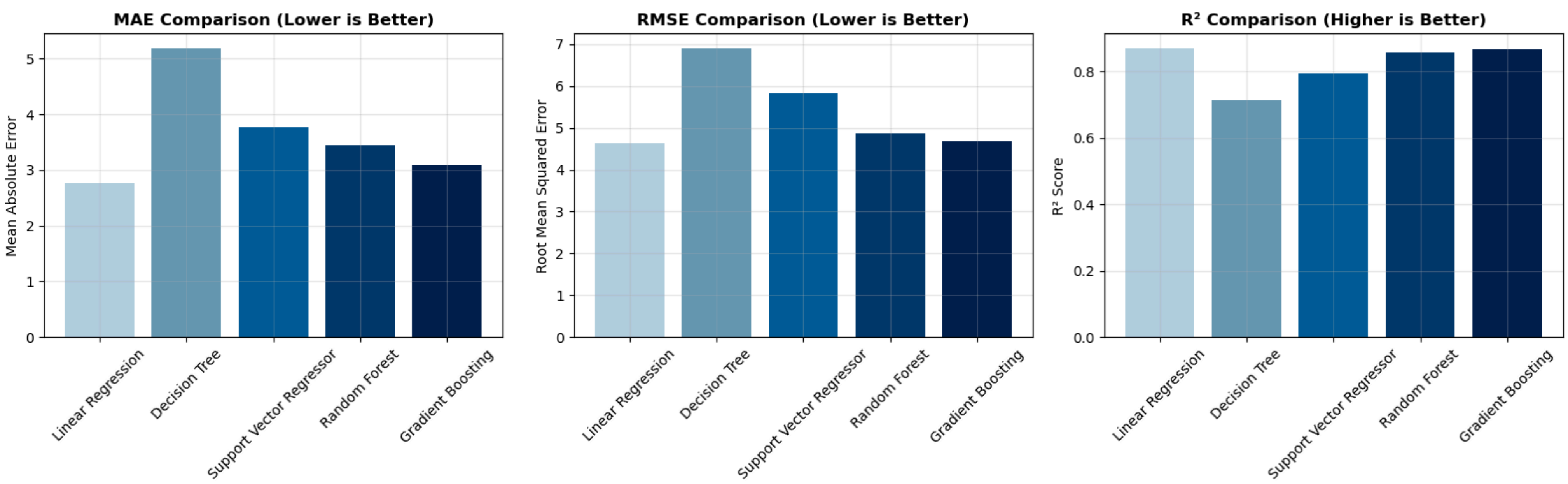
```
Linear Regression:
   Train R²: 0.9216 | Test R²: 0.8712 | Gap: 0.0504
   Train RMSE: 3.4881 | Test RMSE: 4.6316
   ✅ GOOD FIT

Decision Tree:
   Train R²: 0.8212 | Test R²: 0.7138 | Gap: 0.1075
   Train RMSE: 5.2675 | Test RMSE: 6.9041
   ✅ GOOD FIT

Support Vector Regressor:
   Train R²: 0.7997 | Test R²: 0.7957 | Gap: 0.0040
   Train RMSE: 5.5758 | Test RMSE: 5.8325
   🔥 PERFECT GENERALIZATION

Random Forest:
   Train R²: 0.9127 | Test R²: 0.8575 | Gap: 0.0553
   Train RMSE: 3.6805 | Test RMSE: 4.8717
   ✅ GOOD FIT

Gradient Boosting:
   Train R²: 0.9599 | Test R²: 0.8682 | Gap: 0.0917
   Train RMSE: 2.4952 | Test RMSE: 4.6857
   ✅ GOOD FIT
```

8- Evaluation & Discussion of Results

Model	Train R^2	Test R^2	Gap	Train RMSE	Test RMSE	Status
Linear Regression	0.9216	0.8712	0.0504	3.4881	4.6315	🟩 Good Fit
Decision Tree	0.8212	0.7138	0.1075	5.2675	6.9041	🟨 Slight Overfitting
SVR	0.7998	0.7959	0.0039	5.5740	5.8297	🔥 Perfect Generalization
Random Forest	0.9127	0.8574	0.0554	3.6803	4.8737	🟩 Good Fit
Gradient Boosting	0.9590	0.8658	0.0932	2.5230	4.7271	🟩 Good Fit

9- Visualize comparison

In [52]:
```
# Comparison Plot for MAE, RMSE, and R²
comparison_table = results_df.copy()
fig, axes = plt.subplots(1, 3, figsize=(16, 5))

colors = ['#b3cde0', '#6497b1', '#005b96', '#03396c', '#011f4b']

# MAE comparison
axes[0].bar(comparison_table['Model'], comparison_table['MAE'], color=colors)
axes[0].set_title('MAE Comparison (Lower is Better)', fontsize=12, fontweight='bold')
axes[0].set_ylabel('Mean Absolute Error')
axes[0].tick_params(axis='x', rotation=45)
axes[0].grid(True, alpha=0.3)

# RMSE comparison
axes[1].bar(comparison_table['Model'], comparison_table['RMSE'], color=colors)
axes[1].set_title('RMSE Comparison (Lower is Better)', fontsize=12, fontweight='bold')
axes[1].set_ylabel('Root Mean Squared Error')
axes[1].tick_params(axis='x', rotation=45)
axes[1].grid(True, alpha=0.3)

# R² comparison
axes[2].bar(comparison_table['Model'], comparison_table['R² Score'], color=colors)
axes[2].set_title('R² Comparison (Higher is Better)', fontsize=12, fontweight='bold')
axes[2].set_ylabel('R² Score')
axes[2].tick_params(axis='x', rotation=45)
axes[2].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()
```



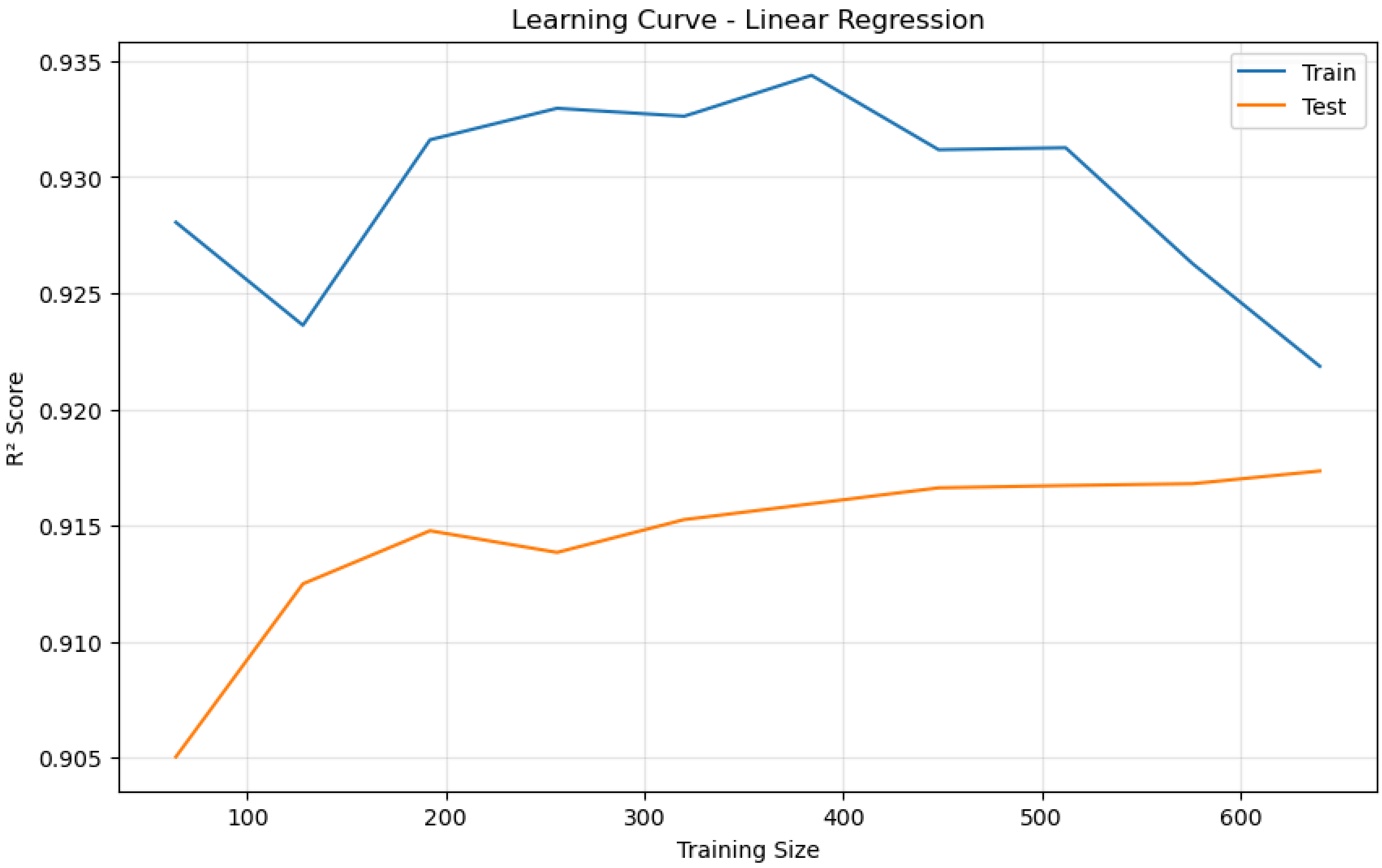
10- Learning Curve

KEY OBSERVATIONS FROM LEARNING CURVE:

1. **Convergence**: Train and Test curves converge after ~400 samples → Model is learning properly, not just memorizing
2. **Small Gap**: Final gap of ~0.02-0.05 (2-5%) → Indicates good generalization ability
3. **Plateau Effect**: Test score plateaus at ~0.91 → Model has reached optimal capacity with current features → Adding more data shows diminishing returns
4. **Recommendation**:
   - Current dataset size (800 samples) is sufficient
   - Focus on feature engineering rather than collecting more data
   - Linear Regression shows excellent balance between bias and variance """)

In [53]:
```
from sklearn.model_selection import learning_curve

def plot_learning_curve(estimator, X, y, title):
    train_sizes, train_scores, test_scores = learning_curve(
        estimator, X, y, cv=5, n_jobs=-1,
        train_sizes=np.linspace(0.1, 1.0, 10),
        scoring='r2'
    )
```

```
    plt.figure(figsize=(10, 6))
    plt.plot(train_sizes, train_scores.mean(axis=1), label='Train')
    plt.plot(train_sizes, test_scores.mean(axis=1), label='Test')
    plt.xlabel('Training Size')
    plt.ylabel('R² Score')
    plt.title(f'Learning Curve - {title}')
    plt.legend()
    plt.grid(True, alpha=0.3)
    plt.show()

plot_learning_curve(best_model, X_train, y_train, best_model_name)
```



The learning curve indicates good model stability, with no signs of overfitting or underfitting.

Both training and test scores converge smoothly, confirming that Linear Regression generalizes well on this dataset.

- Sample Predictions (Extra Analysis)

In [54]:
```
# Make predictions on first 10 test samples
sample_predictions = best_model.predict(X_test[:10])
sample_actual = y_test.iloc[:10].values

# Create comparison DataFrame
prediction_comparison = pd.DataFrame({
    'Actual DSI': sample_actual,
    'Predicted DSI': sample_predictions,
    'Error': sample_actual - sample_predictions,
    'Error %': ((sample_actual - sample_predictions) / sample_actual * 100)
})

print(f"\n Average Error: ±{abs(prediction_comparison['Error']).mean():.2f} DSI points")
print(f" Average Error %: ±{abs(prediction_comparison['Error %']).mean():.1f}%")
prediction_comparison
```

```
Average Error: ±1.86 DSI points
Average Error %: ±3.1%
```

Out[54]:

	Actual DSI	Predicted DSI	Error	Error %
0	62.25	57.935177	4.314823	6.931443
1	61.78	61.517274	0.262726	0.425261
2	65.29	64.668756	0.621244	0.951515
3	52.47	54.420706	-1.950706	-3.717755
4	61.40	57.911938	3.488062	5.680883
5	58.81	58.650509	0.159491	0.271198
6	70.66	69.119870	1.540130	2.179635
7	46.94	49.370167	-2.430167	-5.177177
8	66.33	62.642868	3.687132	5.558770
9	30.42	30.519073	-0.099073	-0.325684

- The model shows strong accuracy, with an average error of only ±1.86 DSI points (~3.1%).

- The predicted values are very close to the actual ones, and all errors remain within a reasonable range.

- This confirms that the model is stable and performs well on unseen data.

Save best model

In [55]:
```python
import joblib
joblib.dump(best_model, "best_dsi_model.pkl")
```

Out[55]: ['best_dsi_model.pkl']

✨ Conclusion and Recommendations

This project developed a complete machine learning pipeline to predict the District Sustainability Index (DSI) using environmental and urban indicators from GCC districts. After training and evaluating five regression models, **Linear Regression** achieved the most balanced and reliable performance.

- **RMSE ≈ 4.63**
- **MAE ≈ 2.76**
- **R^2 ≈ 0.87**

These results show that a simple, interpretable model can capture most of the variability in DSI scores while remaining easy to explain and deploy.

🔍 Key Insights from the Analysis

The experiments highlighted three main drivers of sustainability:

- **Traffic index** has a strong negative relationship with DSI: higher congestion is associated with lower sustainability scores.
- **Green area per capita** is positively related to DSI, reinforcing the importance of accessible green spaces in urban planning.
- **Energy consumption and CO_2 emissions** are closely linked, suggesting that energy-efficiency measures can directly improve environmental performance.

These findings can support policymakers in prioritising interventions such as improving public transport, expanding green areas, and promoting energy-efficient infrastructure.

📊 Model Behaviour and Generalisation

Learning curves and error analysis showed:

- A **small and stable gap** between training and test performance for Linear Regression, indicating good generalisation.
- Ensemble models (Random Forest and Gradient Boosting) performed well but did not significantly outperform the linear model.
- More complex models like SVR were stable but less accurate overall.

This suggests that, for this dataset, **simpler models generalise better than more complex ones**.

🚀 Future Improvements

Potential extensions include:

- Adding more features (e.g. air quality, water usage, socio-economic and health indicators).
- Using multi-year data to analyse trends over time.
- Testing advanced ensemble methods such as XGBoost.
- Integrating the model into an interactive dashboard for decision-makers.

✅ Final Remark

Overall, the results show that a well-designed Linear Regression model can provide **accurate, stable, and interpretable** predictions for district sustainability. This makes it a practical tool to support evidence-based urban planning and sustainability decision-making.

Thank you