# DNI Estimation Model Validation

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The purpose of this notebook is to validate the use of new or current DNI estimation models through multiple steps of analysis

The model input data comes from the published results of the 2021 Blind Modeling Comparison. In the following notebook, the data collected in S2 is used. This data is from the Canadian Solar 275W system at Sandia National Labs in Albuquerque, NM from Jan 2021 - Dec 2021. More information about the dataset can be found at the DuraMAT Data Hub and the published results of the 2021 Blind Modeling Comparison

To demonstrate the way this notebook should work, a pvlib-python model, specifically Dirint, is used in place of a user defined model. To use this notebook for a custom model, simply replace the Dirint model defined in *3: Run model to be validated or import model results*. If the model is run by an external program, it is also possible to import only the results to use in the validation and analysis.

The notebook is segemented into 4 sections:

- **1. Import data from DuraMAT**
- **2. Define relevant system & meteo data**
- **3. Run model to be validated or import model results**
- **4. Compare model to measured results and other baseline models**

In [1]:
```
#import necessary packages and set default formatting for plots

import matplotlib.pyplot as plt #v. 3.7.2
from matplotlib.lines import Line2D #v. 3.7.2
import numpy as np #v. 1.24.3
import seaborn as sns #v 0.12.2
import pandas as pd #v. 2.0.3
import pvlib #v. 0.9.3
import scipy #v. 1.11.1
from tabulate import tabulate #v. 0.8.10

#plotting format
plt.rcParams["figure.figsize"] = (10,6)
plt.rcParams['font.size']=12
plt.rcParams['lines.linewidth']=1.25
plt.rcParams['xtick.labelsize']=12
plt.rcParams['ytick.labelsize']=12
plt.rcParams['axes.titlesize']=12
pd.options.mode.chained_assignment = None
```

## 1. Import data

This section imports the meteo and system data from the DuraMAT Datahub. For the purpose of accurate solar position calculations, the times are set to be labeled at the middle-of-hour. The data includes 2 filters: *bsrn pass* and *SNL No Snow*. The baseline surface radiation network (BSRN) filter follows version 2 quality control tests and the SNL No Snow filter removes any days with recorded snow fall or snow depth. Data is removed if either filter value is '0'. For the meteo data, any 0 values are replaced with NaNs so that statistical values, like mean, are not affected by these values.

In [2]:
```python
# read in data from duramat data hub directly
df = pd.read_excel("https://datahub.duramat.org/dataset/293db0cb-e838-4f7a-8e77-f62e85328c47/resource/b54bdc36-1864-48a9-abab-daf0e3f8dcf5/download/  \
            pvpmc_2021_blind_modeling_comparison_data_s1-s6.xlsx,sheet_name='S2'")
#Reassigning the index so the timesteps are at the middle of the hour
df.index = pd.date_range(start='2021-01-01 00:30:00', end='2021-12-31 23:30:00', freq='H')
df.index = df.index.tz_localize('MST')

#apply the filters that are included in the data & replacing any 0 with nan so they dont affect error metrics
#dropping nans helps keep size down so operations run more quickly and smoothly
df = df.where((df['bsrn_pass'] == 1) & (df['SNL No Snow'] == 1)).dropna()
df.replace(0, np.nan, inplace=True)
df.dropna(inplace=True)

df.head()
```

Out[2]:

| | Scenario | Year | Month | Day | Hour | GHI (W/m2) | DNI (W/m2) | DHI (W/m2) | Ambient Temp (°C) | Relative Humidity (%) | Wind Speed (m/s) | Measured front POA irradiance (W/m2) | Measured module temperature (°C) | Measured DC power (W) | bsrn_pass | SNI Nc Snow |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2021-01-01 08:30:00-07:00** | S2 | 2020.0 | 1.0 | 1.0 | 9.0 | 185.738601 | 754.498236 | 31.546335 | -3.652383 | 54.784333 | 1.803700 | 442.132104 | 6.645174 | 1292.814741 | 1.0 | 1.( |
| **2021-01-01 09:30:00-07:00** | S2 | 2020.0 | 1.0 | 1.0 | 10.0 | 353.666975 | 914.471581 | 40.138926 | -0.708700 | 41.447333 | 2.923567 | 701.031595 | 17.712519 | 2276.603041 | 1.0 | 1.( |
| **2021-01-01 10:30:00-07:00** | S2 | 2020.0 | 1.0 | 1.0 | 11.0 | 482.624408 | 978.551782 | 44.586906 | 0.819633 | 38.089500 | 2.962067 | 879.164182 | 25.669461 | 2782.780150 | 1.0 | 1.( |
| **2021-01-01 11:30:00-07:00** | S2 | 2020.0 | 1.0 | 1.0 | 12.0 | 555.822941 | 1006.709614 | 44.024464 | 2.140700 | 36.223167 | 1.919817 | 977.788429 | 35.226433 | 2989.486270 | 1.0 | 1.( |
| **2021-01-01 12:30:00-07:00** | S2 | 2020.0 | 1.0 | 1.0 | 13.0 | 546.147743 | 865.317214 | 98.340036 | 3.236667 | 35.082167 | 1.641850 | 922.354253 | 38.056121 | 2796.495393 | 1.0 | 1.( |

## 2. Define system and meteo data

'module' is a dictionary of module specific values for 275 W mono-Si Canadian Solar modules and includes system and module data. All data for this system can be found in the various reports on the PVPMC Wesbite. Solar position calculations generate azimuth, zenith, elevation, etc for every timestep in the df

In [3]:
```python
#Defining constants and values that are consistent across all calculations
#we are using S2 from the data, which is the Candian Solar Monocrystalline 275W module
module = {'Tilt': 35,'Latitude': 35.05,'Longitude': -106.54,'Altitude': 1600,'Surface Azimuth': 180,'String Length':12, 'iam0':1,'iam10': 0.9989, 'iam20': 1.0014,
          'iam30': 1.0002, 'iam40':0.9984, 'iam45': 0.9941, 'iam50': 0.9911, 'iam55': 0.9815, 'iam60':0.9631, 'iam65':0.9352, 'iam70':0.8922, 'iam75':0.8134,
          'iam80':0.6778, 'iam85': 0.4351,'U0': 28.825, 'U1': 4.452, 'NOCT': 45, 'Unit Mass': 11.119,'Area':1.621,'Vmp': 31.48 ,'Imp': 8.81,'Voc':38.29 ,
          'Isc': 9.30,'Pmp': 275,'Gamma Pmp': -0.0041,'Alpha Isc':0.0033,'Beta Voc': -0.1178,'Cell Type':'monoSi','Cells in Series':60}
module = pd.Series(module)

#Running solar position calculations
spdf = pvlib.solarposition.get_solarposition(time=df.index, latitude=module['Latitude'],
        longitude=module['Longitude'],temperature=df['Ambient Temp (°C) '], altitude=module['Altitude'])
pres = pvlib.atmosphere.alt2pres(module['Altitude'])
```

```
#Save these values into the df with inputs & results for use in later analysis
df['dni_extra'] = pvlib.irradiance.get_extra_radiation(datetime_or_doy=df.index)
df['Azimuth'] = spdf['azimuth']
df['Zenith'] = spdf['apparent_zenith']
df['Sol Elev'] = spdf['elevation']
df['AOI'] = pvlib.irradiance.aoi(surface_tilt=module['Tilt'], surface_azimuth=module['Surface Azimuth'],solar_zenith=spdf['apparent_zenith'],
        solar_azimuth=spdf['azimuth'])
df['Airmass'] = pvlib.atmosphere.get_relative_airmass(zenith=spdf['apparent_zenith'])
df['Clearness Index'] = pvlib.irradiance.clearness_index(ghi=df['GHI (W/m2)'], solar_zenith=spdf['apparent_zenith'], extra_radiation = df['dni_extra'])
spdf.head()
```

Out[3]:

| | apparent_zenith | zenith | apparent_elevation | elevation | azimuth | equation_of_time |
|---|---|---|---|---|---|---|
| **2021-01-01 08:30:00-07:00** | 77.884310 | 77.950122 | 12.115690 | 12.049878 | 129.546848 | -3.734135 |
| **2021-01-01 09:30:00-07:00** | 69.241432 | 69.279260 | 20.758568 | 20.720740 | 140.756151 | -3.753597 |
| **2021-01-01 10:30:00-07:00** | 62.615700 | 62.643406 | 27.384300 | 27.356594 | 154.026282 | -3.773049 |
| **2021-01-01 11:30:00-07:00** | 58.731118 | 58.754688 | 31.268882 | 31.245312 | 169.230769 | -3.792492 |
| **2021-01-01 12:30:00-07:00** | 58.153100 | 58.176057 | 31.846900 | 31.823943 | 185.427677 | -3.811925 |

Parts of the analysis will require effective irradiance. To calculate this, the pvlib-python `pvlib.irradiance.get_total_irradiance` function with the Perez model is used to get direct and diffuse components of POA. The values are then used in the effective irradiance equation originally defined by King in 2004. To determine IAM values, the coefficients described in the module dictionary & IAM+NMOT Report are used as input into the `pvlib.iam.interp` function. Spectral effects were neglected since there were no module-specific AM coefficients available.

In [4]:

```
#Calculate Environmental Conditions
edf = pvlib.irradiance.get_total_irradiance(surface_tilt=module['Tilt'], surface_azimuth=module['Surface Azimuth'],solar_zenith=spdf['apparent_zenith'],
        solar_azimuth=spdf['azimuth'],dni=df['DNI (W/m2)'], ghi=df['GHI (W/m2)'], dhi=df['DHI (W/m2)'], dni_extra=df['dni_extra'],
                   model ='perez', model_perez='albuquerque1988')
edf['aoi'] = pvlib.irradiance.aoi(surface_tilt=module['Tilt'], surface_azimuth=module['Surface Azimuth'], solar_zenith=spdf['apparent_zenith'],
                solar_azimuth=spdf['azimuth'])
edf['airmass'] = pvlib.atmosphere.get_relative_airmass(zenith=spdf['apparent_zenith'])
edf['am_abs'] = pvlib.atmosphere.get_absolute_airmass(airmass_relative=edf['airmass'], pressure=pres)
df['AOI'] = edf['aoi']

#Calculate Effective Irradiance
ref_thetas= [0,10,20,30,40,45,50,55,60,65,70,75,80,85]
ref_iams = [module['iam0'],module['iam10'],module['iam20'],module['iam30'],module['iam40'],module['iam45'],module['iam50'],
            module['iam55'],module['iam60'],module['iam65'],module['iam70'],module['iam75'],module['iam80'],module['iam85']]
df['IAMs'] = pvlib.iam.interp(aoi=edf['aoi'],theta_ref=ref_thetas,iam_ref=ref_iams )
df['Effective Irradiance'] = (edf['poa_direct'] * df['IAMs'] + edf['poa_diffuse'])
```

# 3. Run the model or import the results to be validated

A model can either be defined and run within this notebook or could be run externally and the results imported below. For demonstration purposes the `pvlib.irradiance.dirint` function is used but should be replaced by the user's model.

In [5]:

```
#Either run a model in this notebook or import the results into the column name below
```

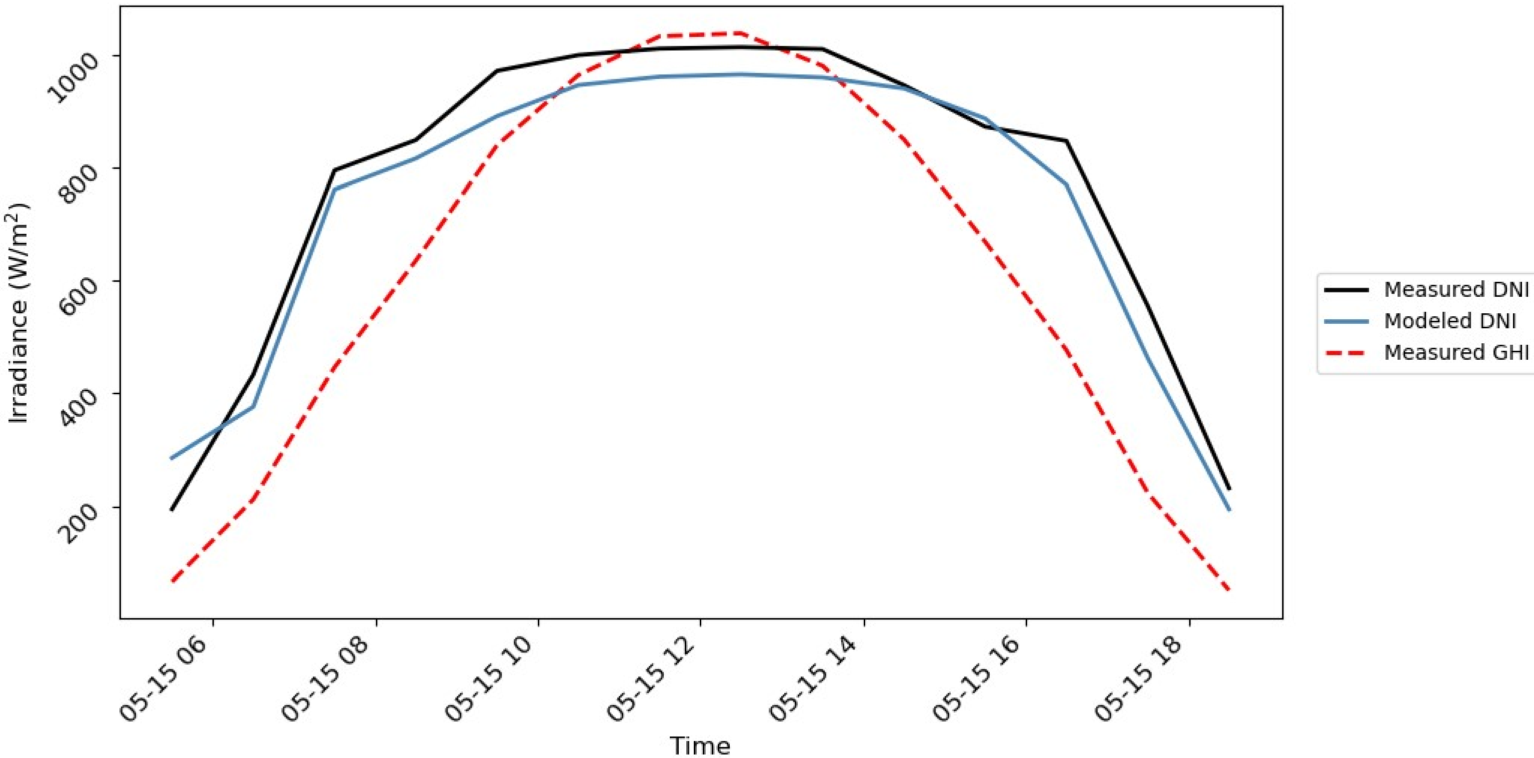
```
#run model here --- this would be replaced by the user's model to be validated but for demonstration purposes a pvlib model is used here
df['Modeled DNI'] = pvlib.irradiance.dirint(ghi=df['GHI (W/m2)'], solar_zenith=df['Zenith'], times=df.index)

# or import model results here --- make sure timestamps line up and are middle-of-hour
# df['Modeled DNI'] = pd.read_excel('results.xlsx')

#specify a model name for use in analysis and plotting
model_name = 'Dirint'
```

## Visualize the results of the model over a sample day

This preliminary check helps make sure the results are feasible and there aren't any obvious extreme errors like time shifts or magnitude differences

In [6]:
```
#diurnal plot
date = '2021-05-15'
fig, ax = plt.subplots()
df.loc[date, 'DNI (W/m2)'].plot(ax=ax, label='Measured DNI', linewidth=2, color='black', zorder=5.5)
df.loc[date, 'Modeled DNI'].plot(ax=ax, label='Modeled DNI', linewidth=2, color='steelblue', zorder=5.5)
df.loc[date, 'GHI (W/m2)'].plot(ax=ax, label='Measured GHI', linewidth=2, color='red', zorder=2.5, linestyle='dashed')

ax.legend(prop=dict(size='small'), loc=[1.03, 0.4])
ax.tick_params(labelrotation=45)
ax.set_ylabel('Irradiance (W/m$^2$)')
ax.set_xlabel('Time')
```

Out[6]:
```
Text(0.5, 0, 'Time')
```




# 4. Compare modeled values to measured values + other baseline models

3 steps of analysis:

- **1. Overall MBE, NMBE, RMSE, NRMSE, and other errors of the model**
- **2. Residual analysis**
- **3. Comparison to baseline model**

## Analysis I: Overall errors of the model

• Mean Bias Error (MBE) - shows the estimation bias of the model

$$\frac{\sum_{i=1}^{N}(V_{modeled} - V_{measured})}{N_{observations}}$$

• Normalized Mean Bias Error (NMBE) - shows the estimation bias of the model in terms of %

$$100 * \frac{\sum_{i=1}^{N}(V_{modeled} - V_{measured})}{\sum_{i=1}^{N}(V_{measured})}$$

- Root Mean Squared Error (RMSE) - measures average difference between modeled and measured values

$$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(V_{modeled} - V_{measured})^2}$$

- Normalized Root Mean Squared Error (NRMSE) - measures average difference between modeled and measured values

$$100 * \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(V_{modeled} - V_{measured})^2}}{\frac{1}{N}V_{measured}}$$

In [7]:

```
nmbe = 100* (df['Modeled DNI'] - df['DNI (W/m2)']).sum()/(df['DNI (W/m2)']).sum()
mbe = (df['Modeled DNI'] - df['DNI (W/m2)']).mean()
rmse = np.sqrt((((df.dropna()['DNI (W/m2)'] - df.dropna()['Modeled DNI'])**2).sum())/(len(df.dropna()['Modeled DNI'])))
nrmse = 100 * rmse/(df['DNI (W/m2)'].mean())
d = [['NMBE', str(round(nmbe,3))+' %'], ['MBE', str(round(mbe,3))+' W'], ['NRMSE', str(round(nrmse,3))+' %'], ['RMSE',str(round(rmse,3))+' W']]
print (tabulate(d, headers=["Metric", "Value"]))
```

```
Metric    Value
--------  ---------
NMBE      -4.503 %
MBE       -29.031 W
NRMSE     11.941 %
RMSE      76.972 W
```

## Plotting the measured vs modeled values

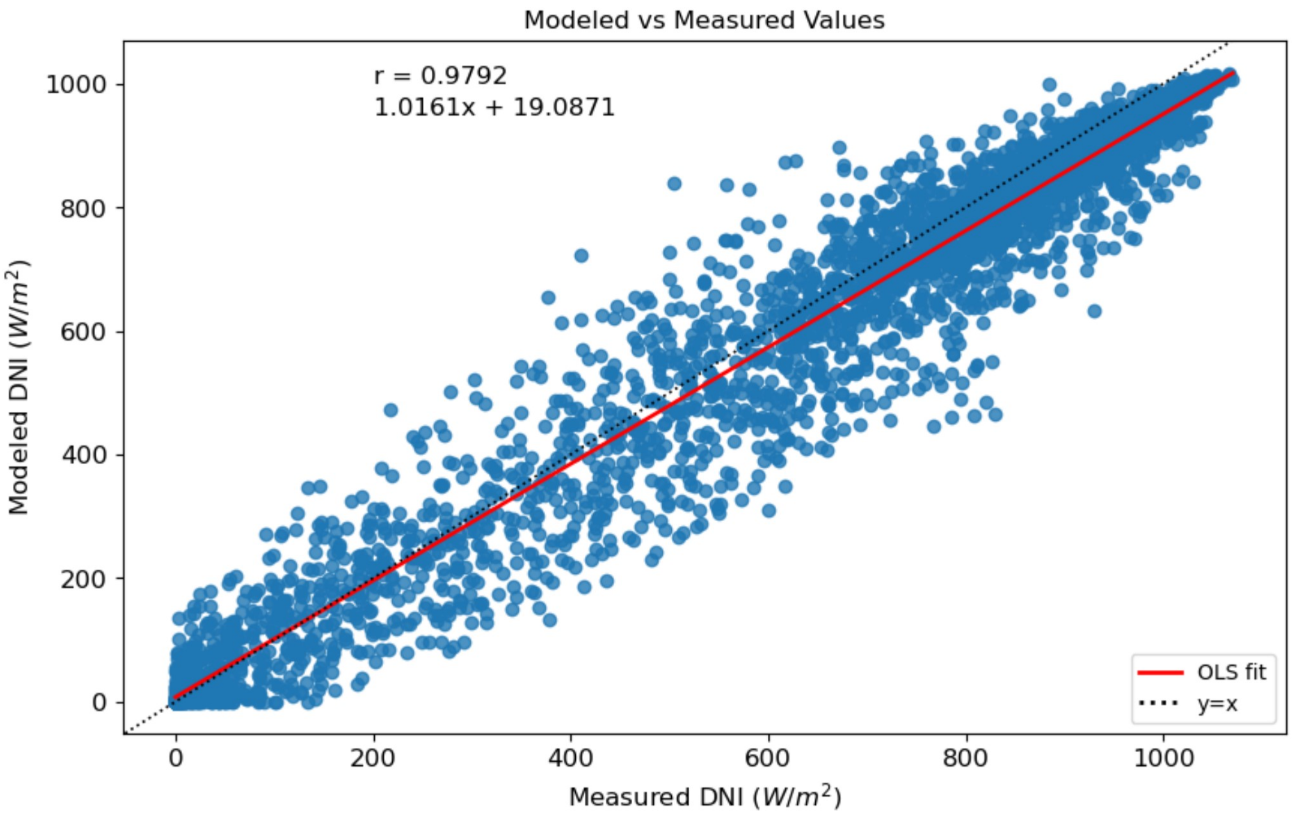
The plot should be mostly linear. r and slope values close to one indicate good correlation and accurate model performance

In [8]:

```
slope, intercept, r, p, std = scipy.stats.linregress(x = df.dropna()['Modeled DNI'], y = df.dropna()['DNI (W/m2)'])
sns.regplot(x = df['DNI (W/m2)'], y = df['Modeled DNI'], line_kws={'color':'red'})
plt.ylabel('Modeled DNI ($W/m^2$)')
plt.xlabel('Measured DNI ($W/m^2$)')
plt.text(200, 1000, s = f"r = {r:0.04f}")
plt.text(200, 950, s = f"{slope:0.04f}x + {intercept:0.04f}")
plt.axline((0, 0), slope=1, c='k', ls=':')
line_1 = Line2D([0], [0], color='red', linewidth=2, linestyle='-',label='OLS fit')
line_2 = Line2D([0], [0], color='k', linewidth=2, linestyle=':',label='y=x')
plt.legend(prop=dict(size='small'), loc='lower right',handles=[line_1, line_2])
plt.title('Modeled vs Measured Values')
```

Out[8]:

```
Text(0.5, 1.0, 'Modeled vs Measured Values')
```




## Energy Yield Estimates

We can run two simulations, one using the DNI model and another using true DNI data to see how much influence the errors of the model have on the overall energy yield

In [9]:

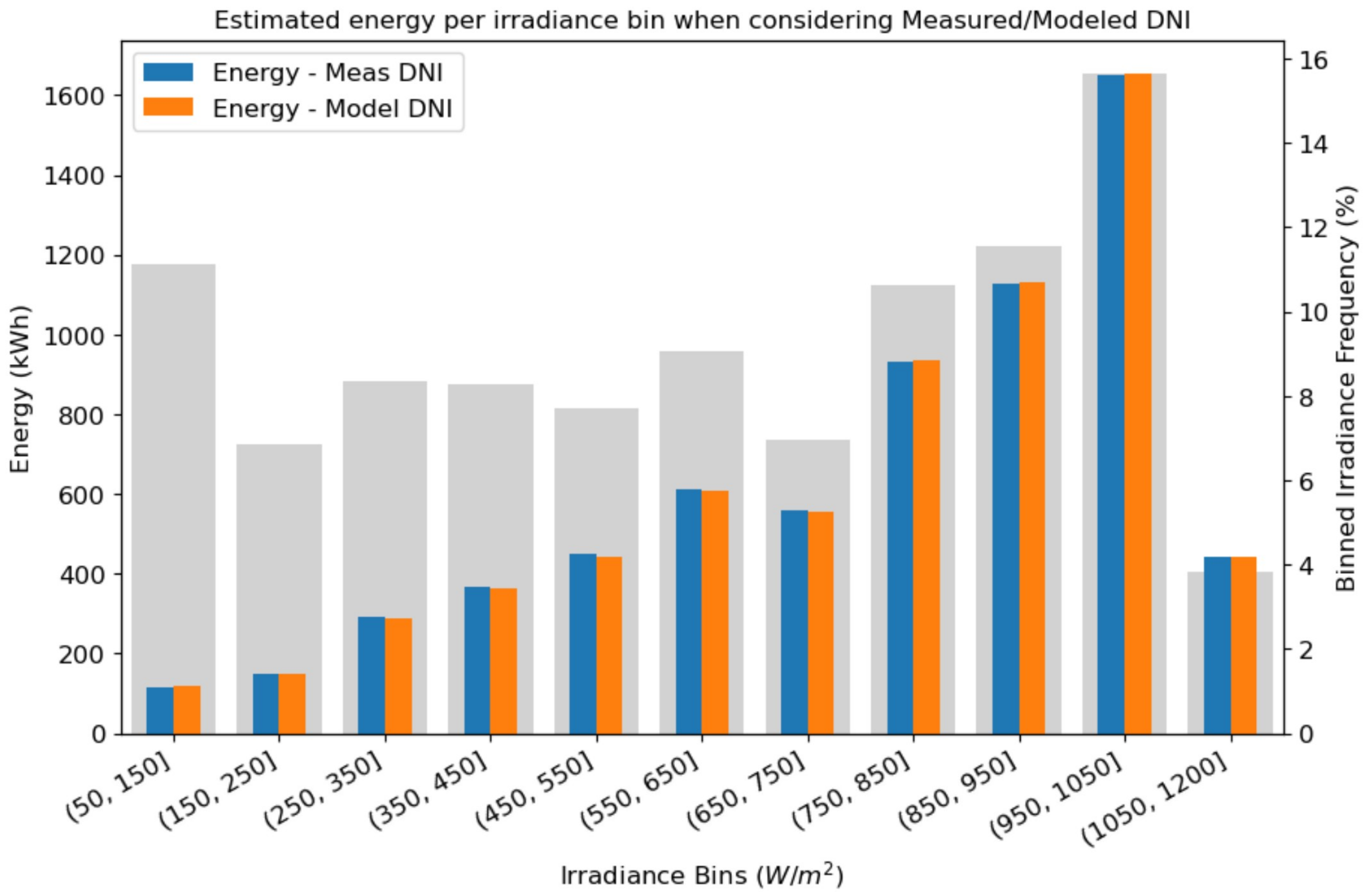
```
#using the effective irradiance calculated with measured DNI to estimate energy
df['DC Power - Meas DNI'] = module['String Length']*pvlib.pvsystem.pvwatts_dc(g_poa_effective=df['Effective Irradiance'],
     temp_cell=pvlib.temperature.sapm_cell_from_module(df['Measured module temperature (°C)'],
                df['Measured front POA irradiance (W/m2)'], deltaT=3),pdc0=module['Pmp'], gamma_pdc=module['Gamma Pmp'])
ann_energy_meas = round(df['DC Power - Meas DNI'].sum()/1000,3)

#calculate POA with modeled DNI to then calculate effective irradiance to estimate energy, using a modeled DHI also since the application for the DNI estimation r
df['Modeled DHI'] = pvlib.irradiance.complete_irradiance(solar_zenith=df['Zenith'], ghi=df['GHI (W/m2)'], dni = df['Modeled DNI'])['dhi']
dni_edf = pvlib.irradiance.get_total_irradiance(surface_tilt=module['Tilt'], surface_azimuth = module['Surface Azimuth'], solar_zenith = df['Zenith'],
                solar_azimuth = df['Azimuth'],dni = df['Modeled DNI'], ghi = df['GHI (W/m2)'], dhi = df['Modeled DHI'], dni_extra=df['dni_extra'],model='perez')
df['Effective Irradiance - Model DNI'] = (dni_edf['poa_direct'] * df['IAMs'] + dni_edf['poa_diffuse'])
df['DC Power - Model DNI'] = module['String Length']*pvlib.pvsystem.pvwatts_dc(g_poa_effective=df['Effective Irradiance - Model DNI'],
                                    temp_cell=pvlib.temperature.sapm_cell_from_module(df['Measured module temperature (°C)'], dni_edf['poa_global'], deltaT=3),
                                    pdc0=module['Pmp'], gamma_pdc=module['Gamma Pmp'])
ann_energy_model = round(df['DC Power - Model DNI'].sum()/1000,3)
#find overall % diff for annual energy
print('With measured DNI, predicted annual energy is',ann_energy_meas ,
```

```
      'kWh and with modeled DNI, predicted annual energy is',ann_energy_model , 'kWh')
print('The % difference in energy estimate when using measured vs modeled DNI is ', round(((ann_energy_meas-ann_energy_model)/ann_energy_model)*100,3),'%')
```

```
With measured DNI, predicted annual energy is 6705.343 kWh and with modeled DNI, predicted annual energy is 6713.082 kWh
The % difference in energy estimate when using measured vs modeled DNI is  -0.115 %
```

In [10]:

```
#we can plot the energy produced in each bin of irradiance and see where the largest differences are when using modeled/measured DNI
df['Irradiance Bins']=(pd.cut(x=df['Measured front POA irradiance (W/m2)'], bins=[50,150,250,350,450,550,650,750,850,950,1050,1200]))
binstr = ['(50, 150]','(150, 250]','(250, 350]','(350, 450]','(450, 550]','(550, 650]','(650, 750]','(750, 850]','(850, 950]','(950, 1050]','(1050, 1200]']

bins = df['Irradiance Bins'].value_counts()
bins = bins.to_frame()
bins = bins.rename(columns = {'count':'Frequency'})
bins['Irradiance Bins'] = bins.index
bins.index.names = ['Index']
bins['Freq Norm'] =( bins['Frequency']/bins['Frequency'].sum()) * 100
bins['Freq Norm'].sum()

bins['Energy - Model DNI'] = df.groupby('Irradiance Bins', observed=False).sum()['DC Power - Model DNI']/1000
bins['Energy - Meas DNI'] = df.groupby('Irradiance Bins', observed=False).sum()['DC Power - Meas DNI']/1000
bins = bins.sort_values('Irradiance Bins')

ax = bins.plot(x="Irradiance Bins", y=["Energy - Meas DNI", "Energy - Model DNI"], kind="bar", rot=0)
plt.xticks(rotation=30, ha='right')
ax.set_ylabel('Energy (kWh)')
ax.set_xlabel('Irradiance Bins ($W/m^2$)')

ax2 = ax.twinx()
ax2 = sns.barplot(x='Irradiance Bins', y='Freq Norm', data=bins, errorbar=None, color='grey', alpha=0.35, zorder=2.5)
ax2.set_ylabel('Binned Irradiance Frequency (%)')
plt.grid(False)
plt.xticks(rotation=30, ha='right')
ax.set_zorder(ax2.get_zorder()+1)
ax.patch.set_visible(False)

plt.title('Estimated energy per irradiance bin when considering Measured/Modeled DNI')
plt.show()
```




## Analysis II: Residual Analysis

- Residual Analysis - quantifies the degree that variables may affect model errors

$$V_{modeled} - V_{measured}$$

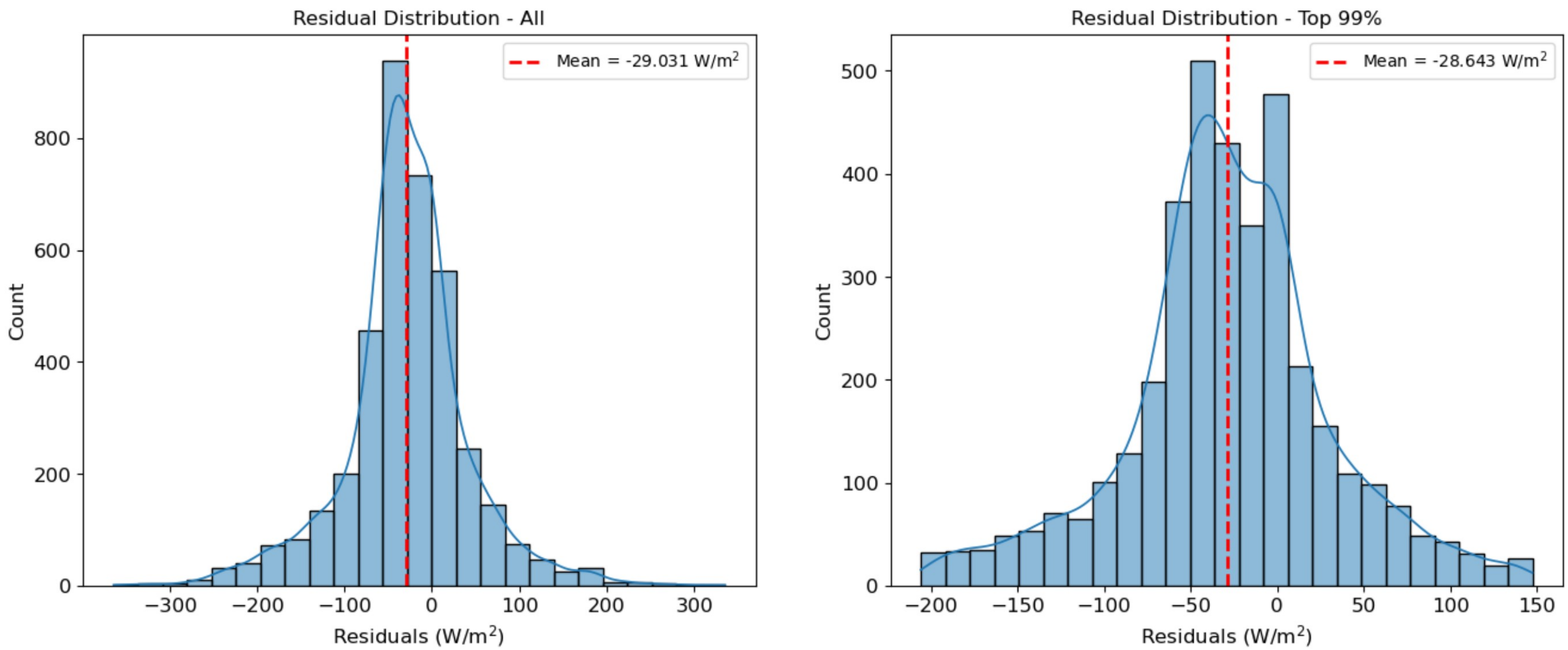
## Residual Distribution

Residuals should be normally distributed, otherwise this indicates a consistent bias of over or under predicting
To get a closer look at a majority of the residuals, the outer 1% are removed using z-score. The distribution should be centered about the mean, shown by the red line

In [11]:
```
fig, (ax1, ax2) = plt.subplots(1,2, figsize=(16,6))

#find residuals
df['Residuals'] = (df['Modeled DNI'] - df['DNI (W/m2)'])
#plot them on histogram
```

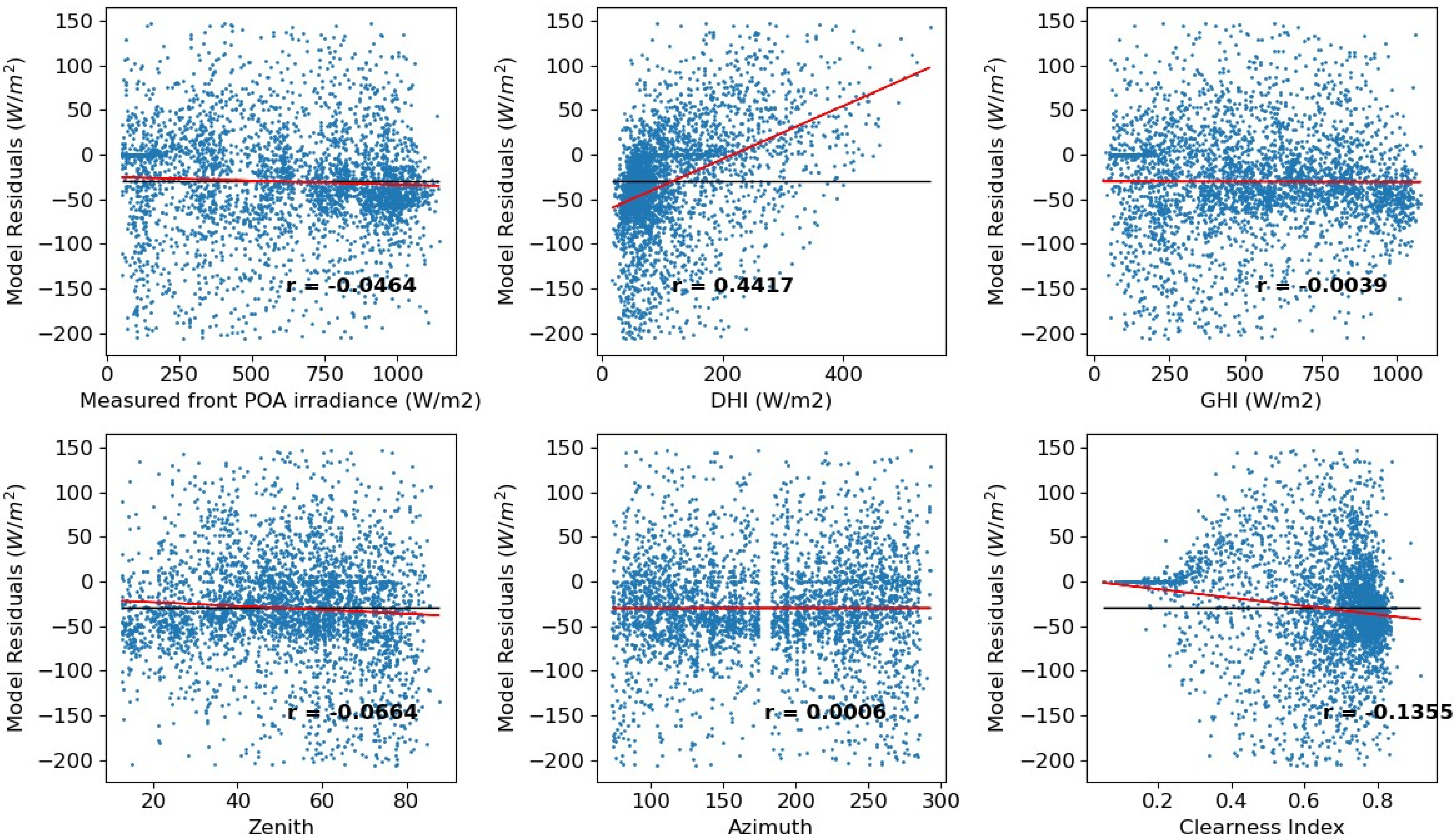
```python
hsp = sns.histplot(df['Residuals'], kde=True, bins=25, ax=ax1)
#add vertical line to show mean
ax1.axvline(x=df['Residuals'].mean(), linewidth=2, color='red',linestyle='--', label =('Mean ='+' '+str(round(df['Residuals'].mean(),3))+' W/m$^2$'))
ax1.set_title('Residual Distribution - All')
ax1.set_xlabel('Residuals (W/m$^2$)')
ax1.legend(prop=dict(size='small'))

#Use z-score to eliminate the outer 1% of residuals
df['zscore'] = scipy.stats.zscore(df['Residuals'].dropna())
df['resid_trim'] = df['Residuals'][(df['zscore'] < 2.5) & (df['zscore'] > -2.5)]
#plot them on histogram
hsp = sns.histplot(df['resid_trim'], kde=True, bins=25, ax=ax2)
#add vertical line to show mean
ax2.axvline(x=df['resid_trim'].mean(), linewidth=2, color='red',linestyle='--',label =('Mean ='+' '+str(round(df['resid_trim'].mean(),3))+' W/m$^2$'))
ax2.set_title('Residual Distribution - Top 99%')
ax2.set_xlabel('Residuals (W/m$^2$)')
ax2.legend(prop=dict(size='small'))
```

Out[11]: <matplotlib.legend.Legend at 0x1b2058b4a60>




In [12]:
```python
#plot residuals against common inputs into DNI models - high correlation could indicate a weakness in the model's consideration of that variable
df = df.dropna()
covariates = ['Measured front POA irradiance (W/m2)', 'DHI (W/m2)', 'GHI (W/m2)','Zenith', 'Azimuth', 'Clearness Index']
y = df['resid_trim']
y_avg = df['resid_trim'].mean()
y_med = df['resid_trim'].median()
```

```python
fig, axes = plt.subplots(2, 3, figsize=(12, 7))
for covariate, ax in zip(covariates, axes.flatten()):
    x = df[covariate]
    z = np.polyfit(x, y, 1)
    p = np.poly1d(z)
    r = np.corrcoef(x, y)[0][1]

    ax.scatter(x, y, s=1)
    ax.hlines(y=y_avg, xmin=x.min(), xmax=x.max(), linewidth=1, color='black', linestyles='-')
    ax.text(x=x.mean(), y=(y.min() + (-0.25*y.min())), s=f"r = {r:0.04f}", weight='bold')
    ax.plot(x, p(x), linewidth=1, color='red')
    ax.set_xlabel(covariate)
    ax.set_ylabel('Model Residuals ($W/m^2$)')

fig.tight_layout()
```

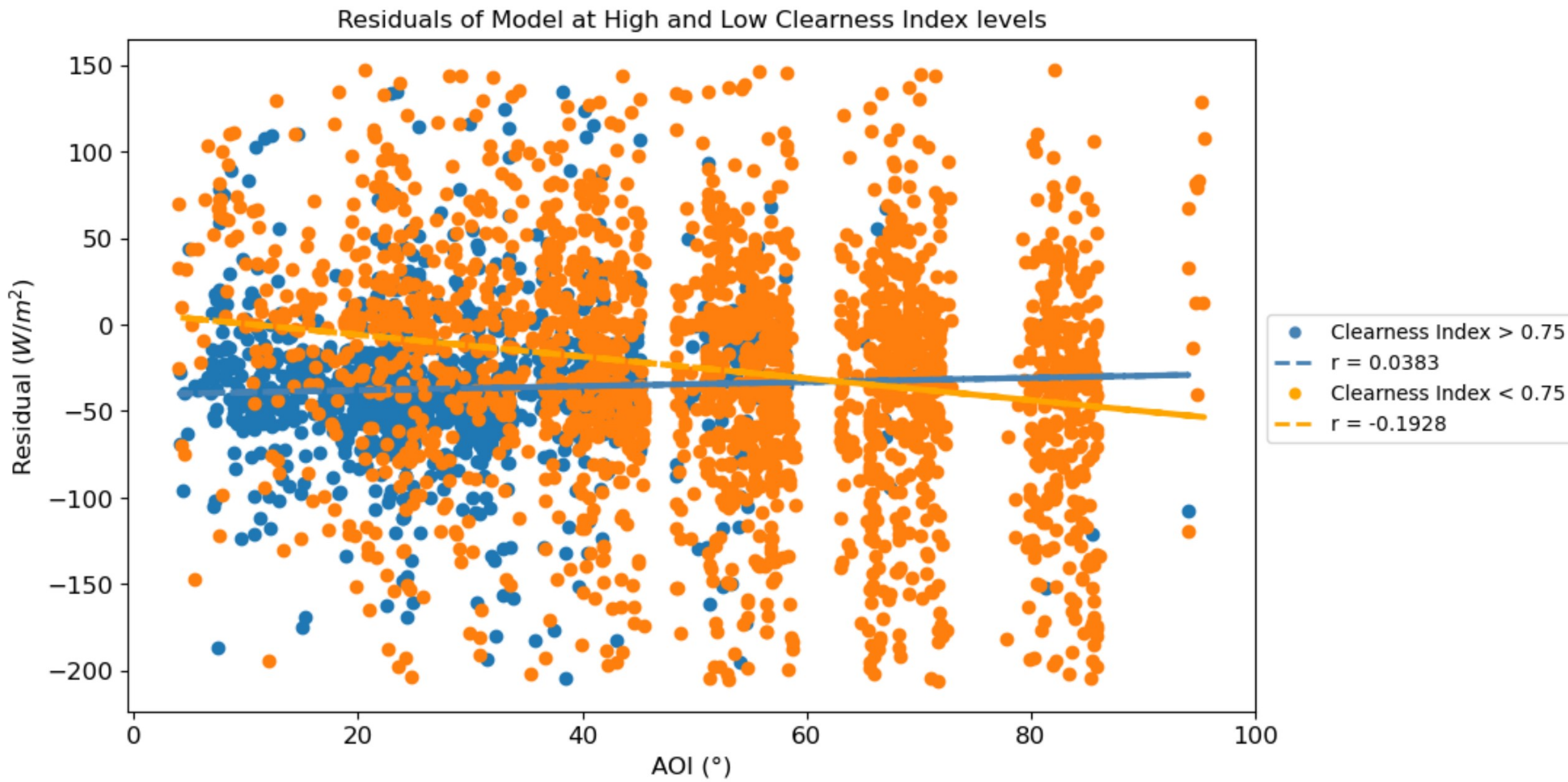


# Plotting residuals vs AOI with division of some metric

Plotting the residuals vs AOI helps to describe the time of day dependence

In [13]:
```
metric = 'Clearness Index' #<---------------- could be any value that is a column in the df (wind speed, clearness index, ambient temp)
bound = 0.75 #<------------------------------ the bound at which to separate the upper and lower categories

df_h = df[df[metric] > bound]
df_l = df[df[metric] < bound]

z_h = np.polyfit(df_h['AOI'],df_h['resid_trim'], 1)
p_h = np.poly1d(z_h)
r_h = np.corrcoef(x=df_h['AOI'], y=df_h['resid_trim'])[0][1]

z_l = np.polyfit(df_l['AOI'],df_l['resid_trim'], 1)
p_l = np.poly1d(z_l)
r_l = np.corrcoef(x=df_l['AOI'], y=df_l['resid_trim'])[0][1]


plt.scatter(x=df_h['AOI'], y=df_h['resid_trim'])
plt.plot(df_h['AOI'], p_h(df_h['AOI']), linewidth=3, color='steelblue',linestyle='--',)
plt.scatter(x=df_l['AOI'], y=df_l['resid_trim'])
plt.plot(df_l['AOI'], p_l(df_l['AOI']), linewidth=3, color='orange',linestyle='--')

plt.ylabel('Residual ($W/m^2$)')
plt.xlabel('AOI (°)')

line_1 = Line2D([], [], color='steelblue',marker='o', linestyle='None',markersize=5, label=(metric+' > '+str(bound)))
line_2 = Line2D([0], [0], color='steelblue', linewidth=2, linestyle='--',label=f"r = {r_h:0.04f}")
line_3 = Line2D([], [], color='orange',marker='o', linestyle='None',markersize=5, label=(metric+' < '+str(bound)))
line_4 = Line2D([0], [0], color='orange', linewidth=2, linestyle='--',label=f"r = {r_l:0.04f}")

lines = [line_1,line_2,line_3,line_4]
plt.legend(prop=dict(size='small'), loc=[1.01, 0.4],handles=lines)
plt.title('Residuals of Model at High and Low '+metric+' levels')
```

Out[13]:
```
Text(0.5, 1.0, 'Residuals of Model at High and Low Clearness Index levels')
```

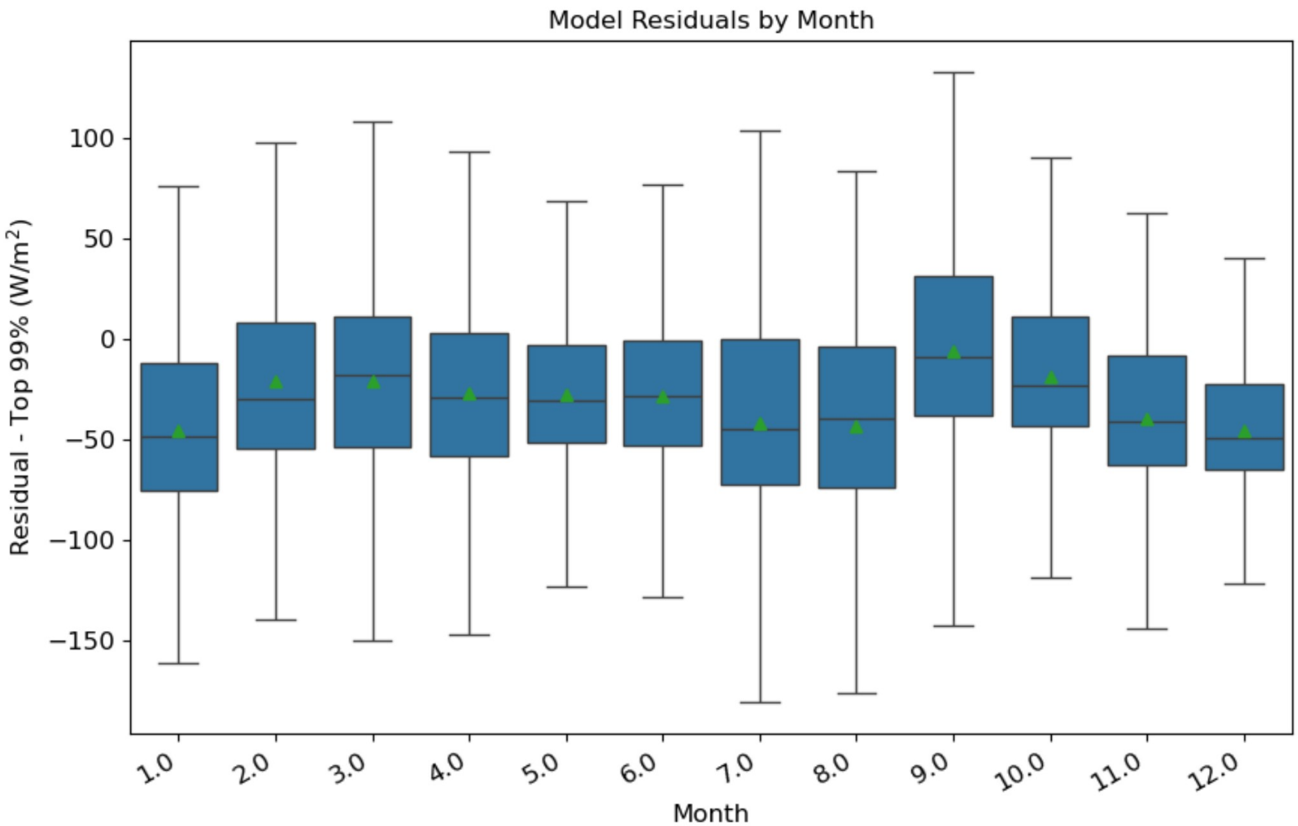



## Residuals by month

Grouping the residuals by month is one way to check if the model has any extreme behavior in specific seasons of the year
This is done below with a boxplot which shows the spread of the data throughout the months

In [14]:
```
sns.boxplot(data=df, x='Month', y='resid_trim', showfliers=False, showmeans=True)
plt.xticks(rotation=30, ha='right')
plt.ylabel('Residual - Top 99% (W/m$^2$)')
plt.title('Model Residuals by Month')
```

Out[14]:
```
Text(0.5, 1.0, 'Model Residuals by Month')
```

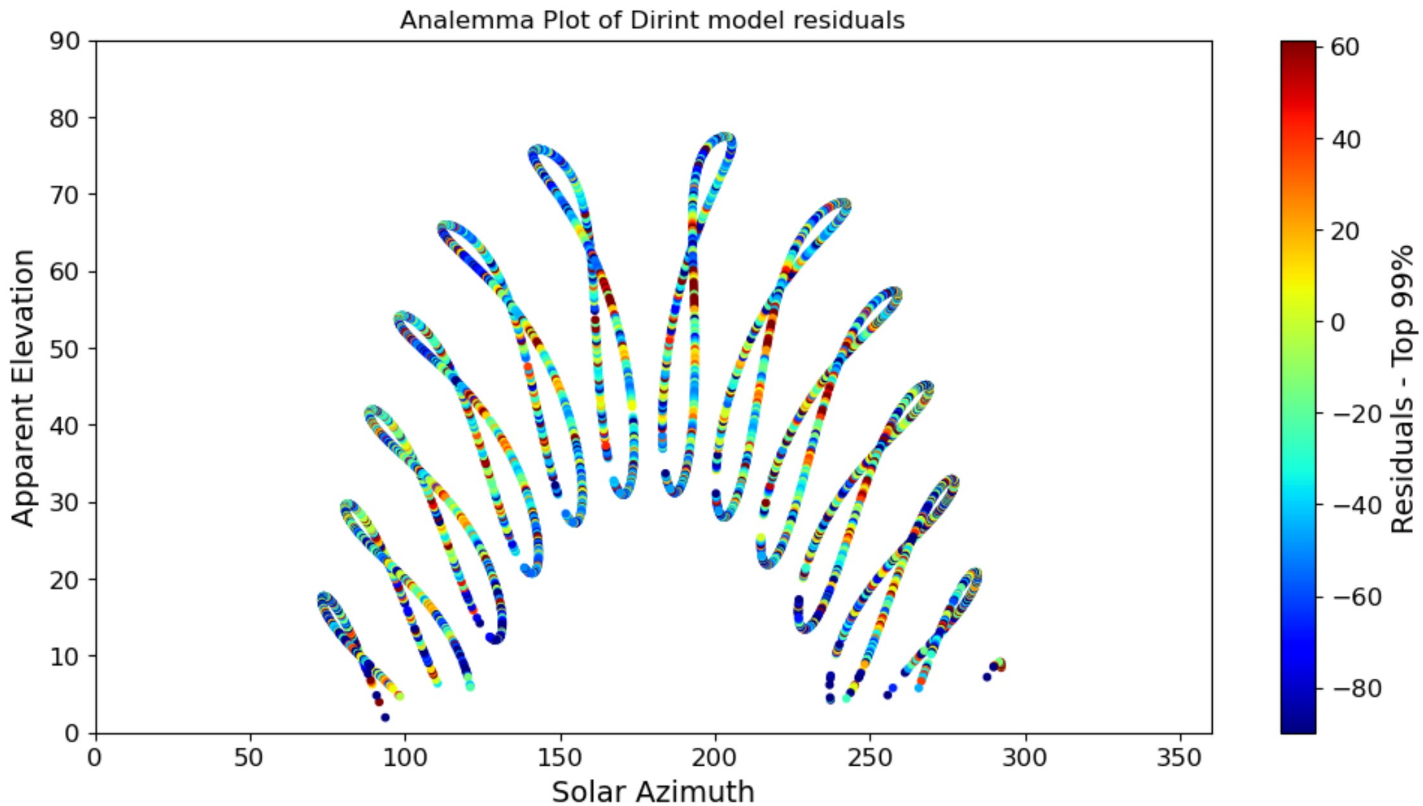



## Analemma Plots

These are another way to check seasonality of a model and can also show how the model performs at specific times of day throughout the entire year

In [15]:
```
#analemma plots show the residuals at different times of the day/year
plt.figure(figsize=(12,6))
plt.scatter(x=df['Azimuth'], y=df['Sol Elev'], c=df['resid_trim'], cmap='jet', s=10)
clb = plt.colorbar()
clb.ax.set_ylabel('Residuals - Top 99%',fontsize =14)
plt.clim((df['resid_trim'].mean() - df['resid_trim'].std()),(df['resid_trim'].quantile(0.75) + df['resid_trim'].std()))
plt.xlim(0,360)
plt.ylim(0,90)
plt.ylabel('Apparent Elevation', fontsize=14 )
plt.xlabel('Solar Azimuth',fontsize =14)
plt.title('Analemma Plot of '+model_name+' model residuals')
```

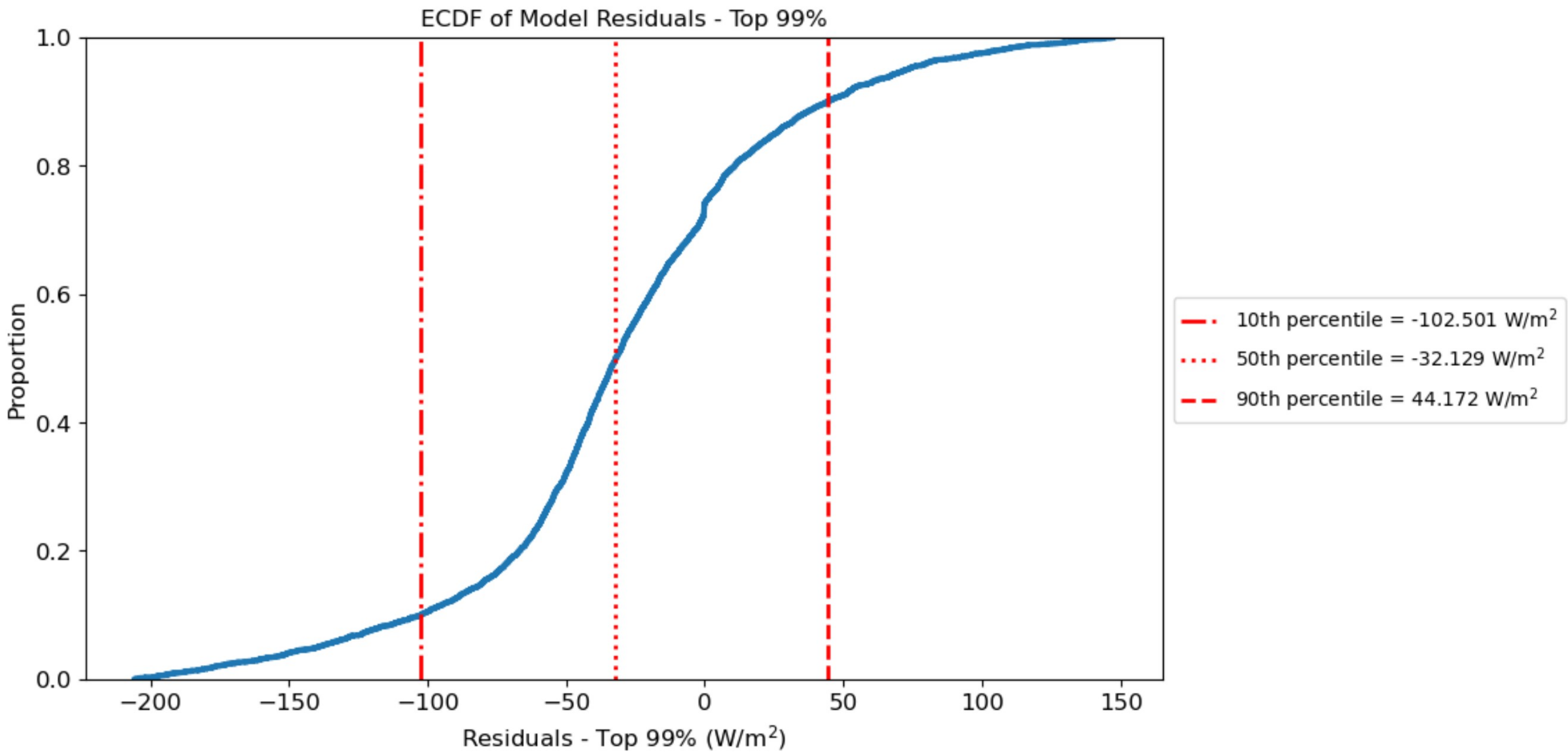
Out[15]:
```
Text(0.5, 1.0, 'Analemma Plot of Dirint model residuals')
```




## Empirical Cumulative Distribution Plot (ECDF)

In [16]:
```
#plot empirical cumulative distribution functions - another way to visualize the distribution of the residuals
sns.ecdfplot(data=df, x='resid_trim', linewidth=3)
plt.xlabel('Residuals - Top 99% (W/m$^2$)')
perc10 = df['resid_trim'].quantile(0.1)
perc50 = df['resid_trim'].quantile(0.5)
perc90 = df['resid_trim'].quantile(0.9)
plt.axvline(perc10, linewidth=2, color='red', linestyle='-.', label=f'10th percentile = {perc10:0.03f} W/m$^2$')
plt.axvline(perc50, linewidth=2, color='red', linestyle='dotted', label=f'50th percentile = {perc50:0.03f} W/m$^2$')
plt.axvline(perc90, linewidth=2, color='red', linestyle='--', label=f'90th percentile = {perc90:0.03f} W/m$^2$')
plt.legend(prop=dict(size='small'), loc=[1.01, 0.4])
plt.title('ECDF of Model Residuals - Top 99%')
```

Out[16]:
```
Text(0.5, 1.0, 'ECDF of Model Residuals - Top 99%')
```



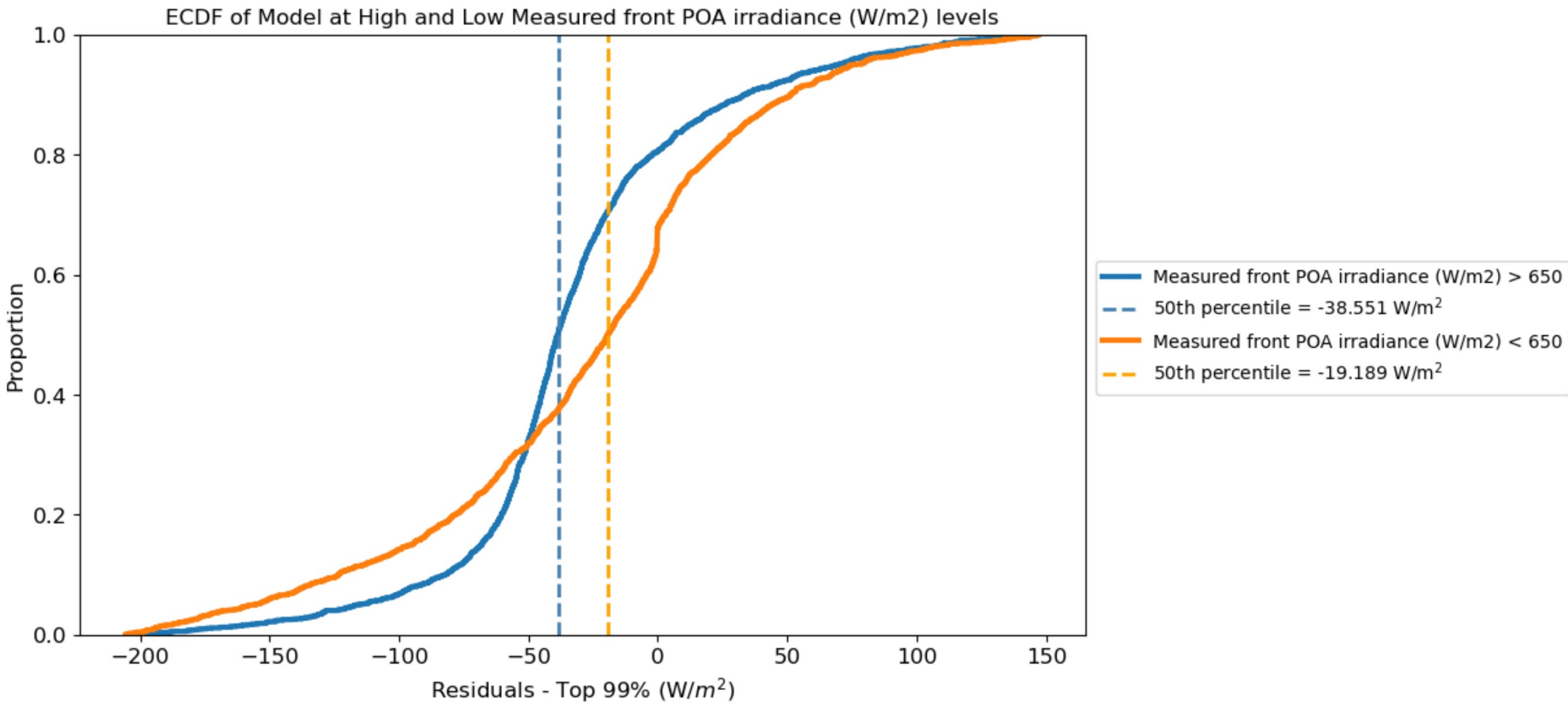

Plotting ECDF of model residuals with the division of some metric

In [17]:

```
metric = 'Measured front POA irradiance (W/m2)' #<---------------- could be any value that is a column in the df (wind speed, clearness index, ambient temp)
bound = 650 #<----------------------------- the bound at which to separate the upper and lower categories

df_h = df[df[metric] > bound]
df_l = df[df[metric] < bound]

perc50_h = df_h['resid_trim'].quantile(0.5)
perc50_l = df_l['resid_trim'].quantile(0.5)

sns.ecdfplot(data=df_h, x='resid_trim', linewidth=3, label=(metric+' > '+str(bound)))
plt.axvline(perc50_h, linewidth=2, color='steelblue', linestyle='--', label=f'50th percentile = {perc50_h:0.03f} W/m$^2$')
sns.ecdfplot(data=df_l, x='resid_trim', linewidth=3, label = (metric+' < '+str(bound)))
plt.axvline(perc50_l, linewidth=2, color='orange', linestyle='--', label=f'50th percentile = {perc50_l:0.03f} W/m$^2$')
plt.legend(prop=dict(size='small'), loc=[1.01, 0.4])
plt.xlabel('Residuals - Top 99% (W/$m^2$)')
plt.title('ECDF of Model at High and Low '+metric+' levels')
```

Out[17]:

```
Text(0.5, 1.0, 'ECDF of Model at High and Low Measured front POA irradiance (W/m2) levels')
```




## Analysis III: Comparison to Baseline Models

Comparing the model to other well-known baseline models can provide information about how the model is performing relative to accepted models. The baseline model chosen for DNI estimation is `pvlib.irradiance.disc`

In [18]:
```
#calculate baseline model DNI estimate
df['Baseline Model DNI'] = pvlib.irradiance.disc(ghi=df['GHI (W/m2)'], solar_zenith=df['Zenith'], datetime_or_doy = df.index)['dni']
#calculate the residuals of the baseline model
df['Baseline Residuals'] = df['Baseline Model DNI'] - df['DNI (W/m2)']
baseline_model = 'Disc'
```

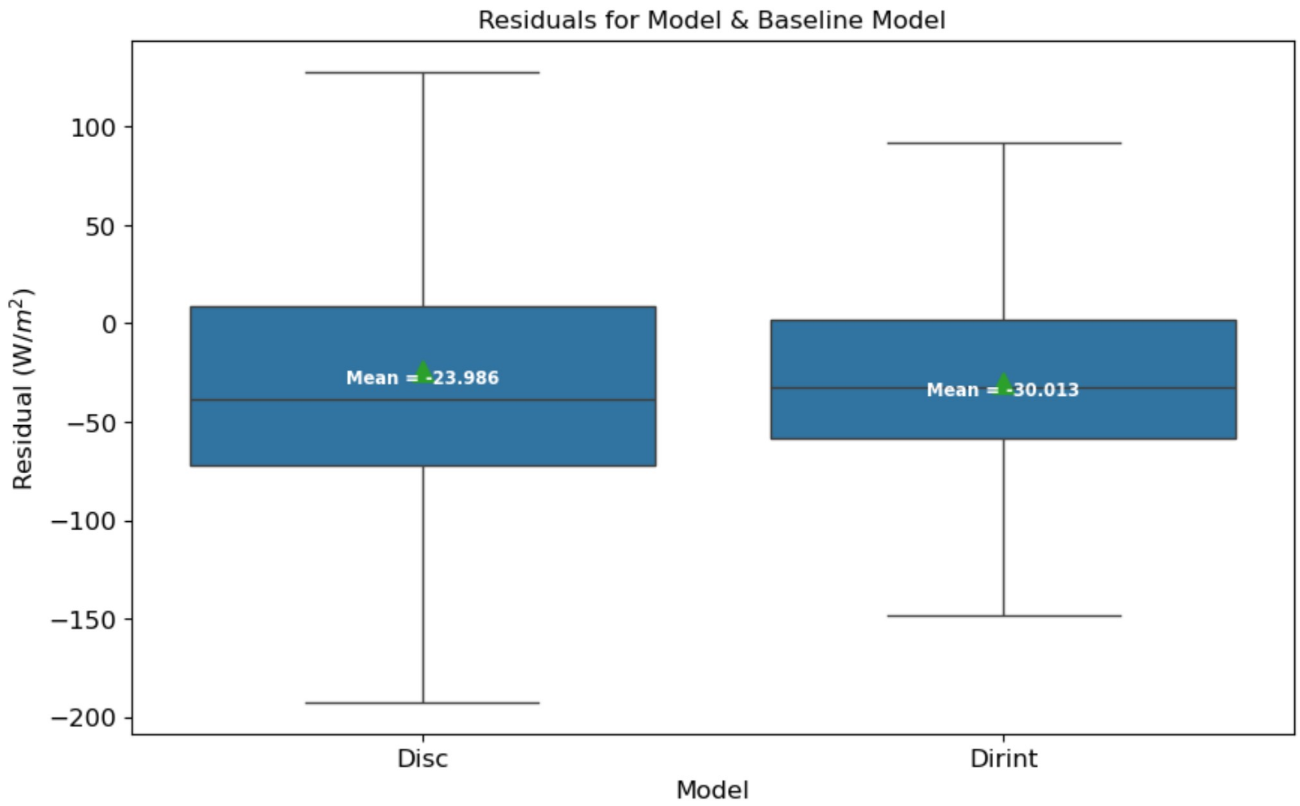
In [19]:
```
#calculate POA with the baseline modeled DNI to use in calculating effective irradiance to estimate energy, again estimating DHI as well
df['Baseline Model DHI'] = pvlib.irradiance.complete_irradiance(solar_zenith=df['Zenith'], ghi=df['GHI (W/m2)'], dni = df['Baseline Model DNI'])['dhi']
bdni_df = pvlib.irradiance.get_total_irradiance(surface_tilt=module['Tilt'], surface_azimuth = module['Surface Azimuth'], solar_zenith = df['Zenith'],
              solar_azimuth = df['Azimuth'], dni = df['Baseline Model DNI'], ghi = df['GHI (W/m2)'], dhi = df['Baseline Model DHI'],
                    dni_extra=df['dni_extra'],model='perez')
df['Effective Irradiance - Baseline Model DNI'] = (bdni_df['poa_direct'] * df['IAMs'] + bdni_df['poa_diffuse'])
df['DC Power - Baseline Model DNI'] = module['String Length']*pvlib.pvsystem.pvwatts_dc(g_poa_effective=df['Effective Irradiance - Baseline Model DNI'],
                    temp_cell=pvlib.temperature.sapm_cell_from_module(df['Measured module temperature (°C)'],
                    bdni_df['poa_global'], deltaT=3), pdc0=module['Pmp'], gamma_pdc=module['Gamma Pmp'])
ann_energy_baseline = round(df['DC Power - Baseline Model DNI'].sum()/1000,3)
```

In [20]:
```
#find overall % diff for annual energy
print('With the initial DNI estimation model, predicted annual energy is', ann_energy_model,
      'kWh and with the baseline modeled DNI, predicted annual energy is',ann_energy_baseline , 'kWh')
print('The % difference in energy estimate when using the initial model vs the baseline DNI estimation model ',
      round(((ann_energy_baseline-ann_energy_model)/ann_energy_model)*100,3),'%')
```

```
With the initial DNI estimation model, predicted annual energy is 6713.082 kWh and with the baseline modeled DNI, predicted annual energy is 6493.727 kWh
The % difference in energy estimate when using the initial model vs the baseline DNI estimation model  -3.268 %
```

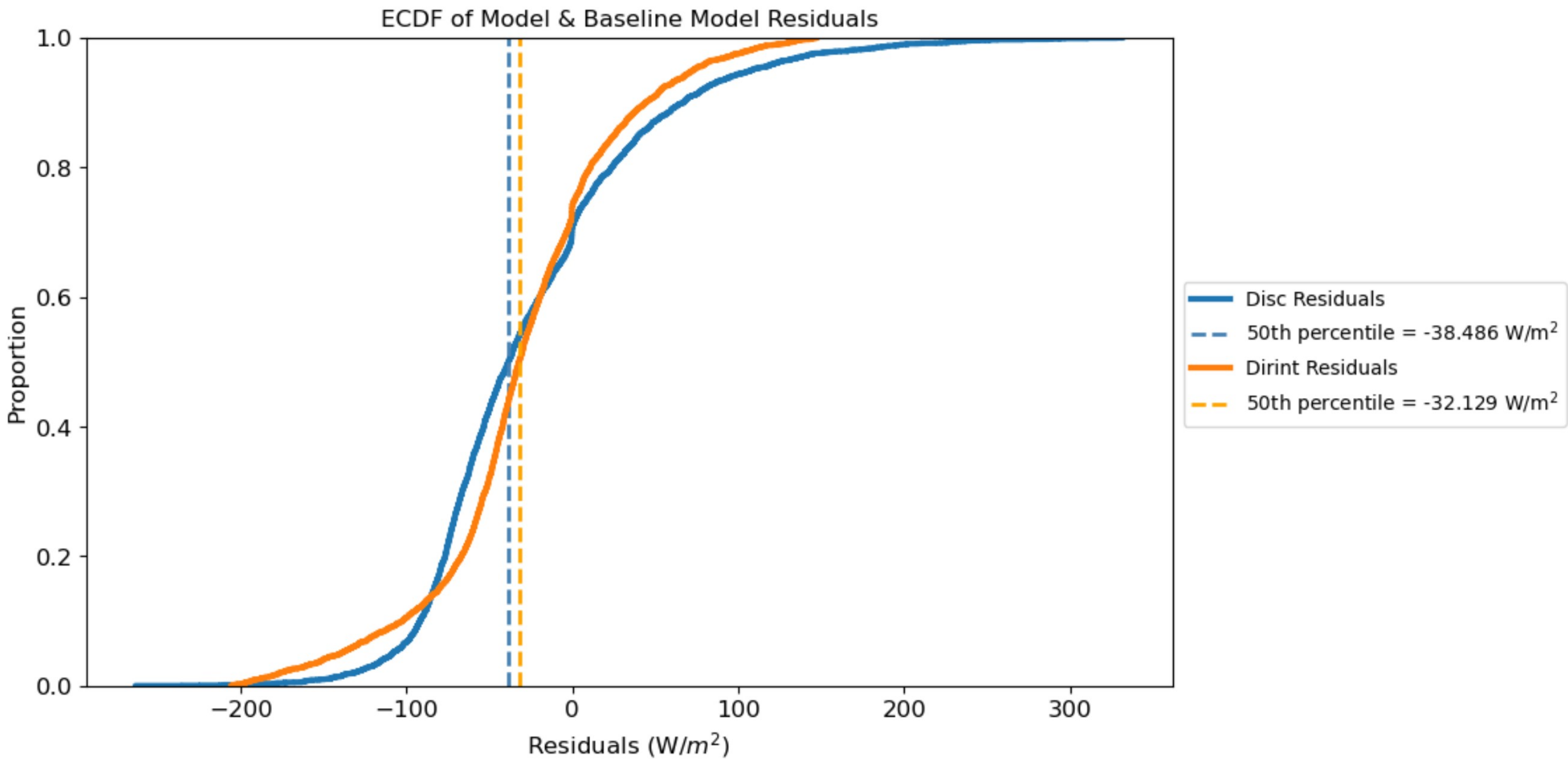
In [21]:
```
#put the model and baseline model residuals in one df for easy analysis
resid_df = pd.concat([
    pd.DataFrame({'Residual': df['Baseline Model DNI'] - df['DNI (W/m2)'], 'Model': baseline_model,}),
    pd.DataFrame({'Residual': df['Modeled DNI'] - df['DNI (W/m2)'],'Model':model_name ,})
], ignore_index=True)

box_plot = sns.boxplot(x='Model', y='Residual', data=resid_df, showfliers=False, showmeans=True, meanprops={'markersize':10})
plt.ylabel('Residual (W/$m^2$)')
#view the numerical value of mean on plot
means = resid_df.groupby(['Model'])['Residual'].mean()
vertical_offset = resid_df['Residual'].mean() * 0.25 # offset from median for display
for xtick in box_plot.get_xticks():
    if xtick == 0:
        name = baseline_model
    else:
        name = model_name
    box_plot.text(xtick,means[name] + vertical_offset,('Mean = '+str(round(means[name],3))),horizontalalignment='center',size='x-small',color='w',weight='semibolc
plt.title('Residuals for Model & Baseline Model')
```

Out[21]: Text(0.5, 1.0, 'Residuals for Model & Baseline Model')

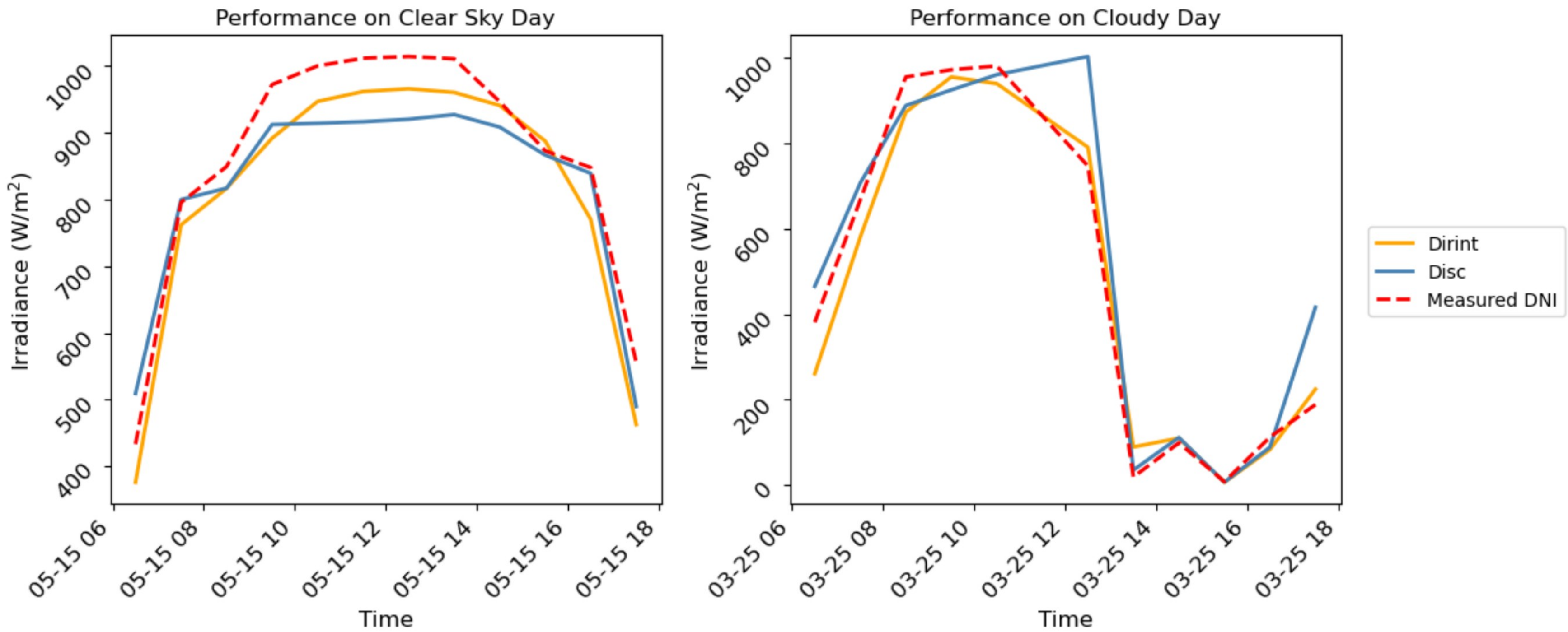



In [22]:
```
#ecdf of the two models overlayed & p50 for each

perc50_m = np.percentile(df['Residuals'].dropna(), 50)
perc50_b = np.percentile(df['Baseline Residuals'].dropna(), 50)

sns.ecdfplot(data=df, x='Baseline Residuals', linewidth=3, label = (baseline_model+' Residuals'))
plt.axvline(x=perc50_b, linewidth=2, color='steelblue', linestyle='--', label=f'50th percentile = {perc50_b:0.03f} W/m$^2$')
sns.ecdfplot(data=df, x='Residuals', linewidth=3, label=(model_name+' Residuals'))
plt.axvline(x=perc50_m, linewidth=2, color='orange', linestyle='--', label=f'50th percentile = {perc50_m:0.03f} W/m$^2$')
plt.legend(prop=dict(size='small'), loc=[1.01, 0.4])
plt.xlabel('Residuals (W/$m^2$)')
plt.title('ECDF of Model & Baseline Model Residuals')
```

Out[22]:
```
Text(0.5, 1.0, 'ECDF of Model & Baseline Model Residuals')
```



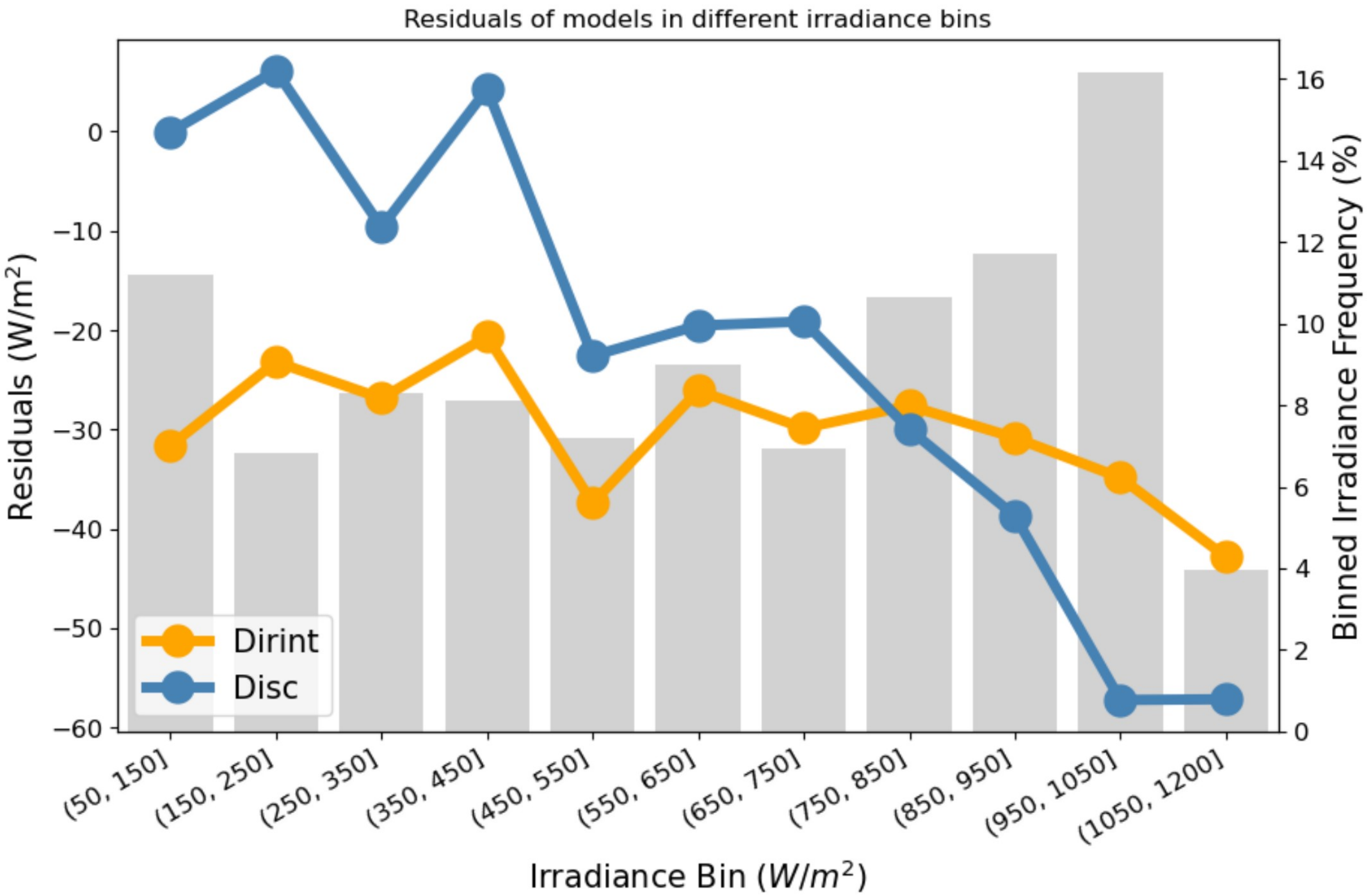

In [23]:
```python
# diurnal plots help visualize the differences between modeled and measured DNI as well as model and baseline model DNI performance

dates = [('Clear Sky', '2021-05-15'),('Cloudy', '2021-03-25'),]

fig, axes = plt.subplots(1, len(dates), figsize=(12,5))

for (sky_condition, date), ax in zip(dates, axes):
    df.loc[date, 'Modeled DNI'].plot(ax=ax, linewidth=2, color='orange', label = model_name)
    df.loc[date, 'Baseline Model DNI'].plot(ax=ax, linewidth=2, color='steelblue',label = baseline_model)
    df.loc[date, 'DNI (W/m2)'].plot(ax=ax, linewidth=2, linestyle='dashed', color='red', label = 'Measured DNI')
    ax.tick_params(labelrotation = 45)
    ax.set_ylabel('Irradiance (W/m$^2$)')
    ax.set_xlabel('Time')
    ax.set_title(f'Performance on {sky_condition} Day')

axes[-1].legend(prop=dict(size='small'), loc=[1.05, 0.4])
fig.tight_layout()
```




In [25]:
```
#view the model and baseline model performance at different levels of irradiance

df['Irradiance Bins']=(pd.cut(x=df['Measured front POA irradiance (W/m2)'], bins=[50,150,250,350,450,550,650,750,850,950,1050,1200]))
binstr = ['(50, 150]','(150, 250]','(250, 350]','(350, 450]','(450, 550]','(550, 650]','(650, 750]','(750, 850]','(850, 950]','(950, 1050]','(1050, 1200]']

bins = df['Irradiance Bins'].value_counts().to_frame()
bins = bins.rename(columns = {'count':'Frequency'})
bins['Irradiance Bins'] = bins.index
bins.index.names = ['Index']
bins['Freq Norm'] =( bins['Frequency']/bins['Frequency'].sum()) * 100
bins['Freq Norm'].sum()

fig, ax = plt.subplots()
x = binstr
y = df[['Irradiance Bins','Residuals']].groupby('Irradiance Bins', observed=False).mean().sort_values('Irradiance Bins')['Residuals']
ax.plot(x, y, 'orange', marker='o', zorder=6.5, linewidth=5, markersize=15)
y = df[['Irradiance Bins','Baseline Residuals']].groupby('Irradiance Bins', observed=False).mean().sort_values('Irradiance Bins')['Baseline Residuals']
ax.plot(x, y, 'steelblue', marker='o', zorder=6.5, linewidth=5, markersize=15)
plt.xticks(rotation=30, ha='right')

ax.set_ylabel('Residuals (W/m$^2$)', fontsize=15)
ax.set_xlabel('Irradiance Bin ($W/m^2$)', fontsize=15)
ax.legend([model_name,baseline_model],loc='lower left', fontsize=15)

ax2 = ax.twinx()
ax2 = sns.barplot(x='Irradiance Bins', y='Freq Norm', data=bins, errorbar=None, color='grey', alpha=0.35, zorder=2.5)
ax2.set_ylabel('Binned Irradiance Frequency (%)', fontsize=15)
```

```
plt.grid(False)
plt.xticks(rotation=30, ha='right')
ax.set_zorder(ax2.get_zorder()+1)
ax.patch.set_visible(False)
plt.title('Residuals of models in different irradiance bins')
```

Out[25]: Text(0.5, 1.0, 'Residuals of models in different irradiance bins')




In [ ]:

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In [ ]: