# Extracting Solar Visible and Infrared Irradiance Data from Typical Weather File for Solar Building Design and Simulation

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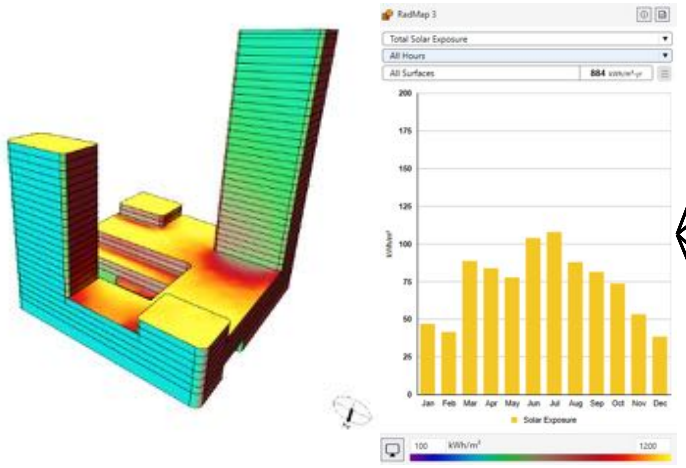
Introduction

# Typical Solar Analysis for building application:



**<u>Geographical and Site-Specific Data</u>**

- Geographical location
- Building orientation, topography
- Climate data

**<u>Building Information</u>**

- 3D model
- Materials used
- Window, shading devices

**<u>Analysis Tools</u>**

- Such as EnergyPlus, IES VE, Ladybug & Honeybee, etc.

**<u>Solar Devices Specifications</u>**

- For example, sizes, efficiency and cost of solar panels

**But!**

*What if solar devices are spectral-dependent?*

Introduction

## TMY3 data format

| Field | Element | Unit or Range | Resolution | Description |
|---|---|---|---|---|
| 1 | Date | MM/DD/YYYY | -- | Date of data record |
| 2 | Time | HH:MM | -- | Time of data record (local standard time) |
| 3 | Hourly extraterrestrial radiation on a horizontal surface | Watt-hour per square meter | 1 Wh/m² | Amount of solar radiation received on a horizontal surface at the top of the atmosphere during the 60-minute period ending at the timestamp |
| 4 | Hourly extraterrestrial radiation normal to the sun | Watt-hour per square meter | 1 Wh/m² | Amount of solar radiation received on a surface normal to the sun at the top of the atmosphere during the 60-minute period ending at the timestamp |
| 5 | Global horizontal irradiance | Watt-hour per square meter | 1 Wh/m² | Total amount of direct and diffuse solar radiation received on a horizontal surface during the 60-minute period ending at the timestamp |
| 6 | Global horizontal irradiance source flag | 1-2 | -- | See Table 1-4 |
| 7 | Global horizontal irradiance uncertainty | Percent | 1% | Uncertainty based on random and bias error estimates – see NSRDB User's Manual (Wilcox, 2007b) |
| 8 | Direct normal irradiance | Watt-hour per square meter | 1 Wh/m² | Amount of solar radiation (modeled) received in a collimated beam on a surface normal to the sun during the 60-minute period ending at the timestamp |
| 9 | Direct normal irradiance source flag | 1-2 | -- | See table 1-4 |
| 10 | Direct normal irradiance uncertainty | Percent | 1% | Uncertainty based on random and bias error estimates – see NSRDB User's Manual (Wilcox, 2007b) |
| 11 | Diffuse horizontal irradiance | Watt-hour per square meter | 1 Wh/m² | Amount of solar radiation received from the sky (excluding the solar disk) on a horizontal surface during the 60-minute period ending at the timestamp |
| 12 | Diffuse horizontal irradiance source flag | 1-2 | -- | See Table 1-4 |
| 13 | Diffuse horizontal irradiance uncertainty | Percent | 1% | Uncertainty based on random and bias error estimates – see NSRDB User's Manual (Wilcox, 2007b) |

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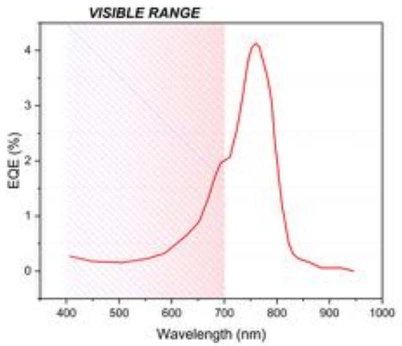
***Introduce narrowband solar components into weather files to perform modified building solar analysis***




*Consider such wavelength-selective transparent PV solar cell. It has a general PCE=0.4% and AVT=88.3% (measured under AM1.5 Solar Illuminator), by using conventional weather files, its spectral-selectivity may not be fully considered and understood*

# Existing tools

SMARTS

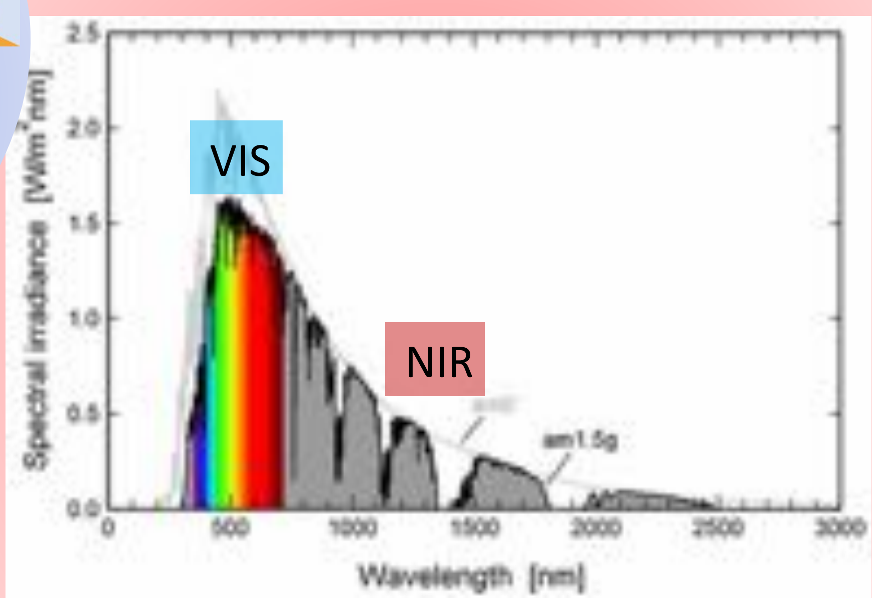
**Radiative Transfer Model**

Spectral Sciences Inc.

MODTRAN®

Advantage:
- Model flexibility
- Physically based
- Detailed spectral information

Limitation:
- Hard-to-get atmospheric factors
- Difficult to update real-time
- Model uncertainty




**Ground-based measurement**

Advantage:
- Direct measurement
- High accuracy

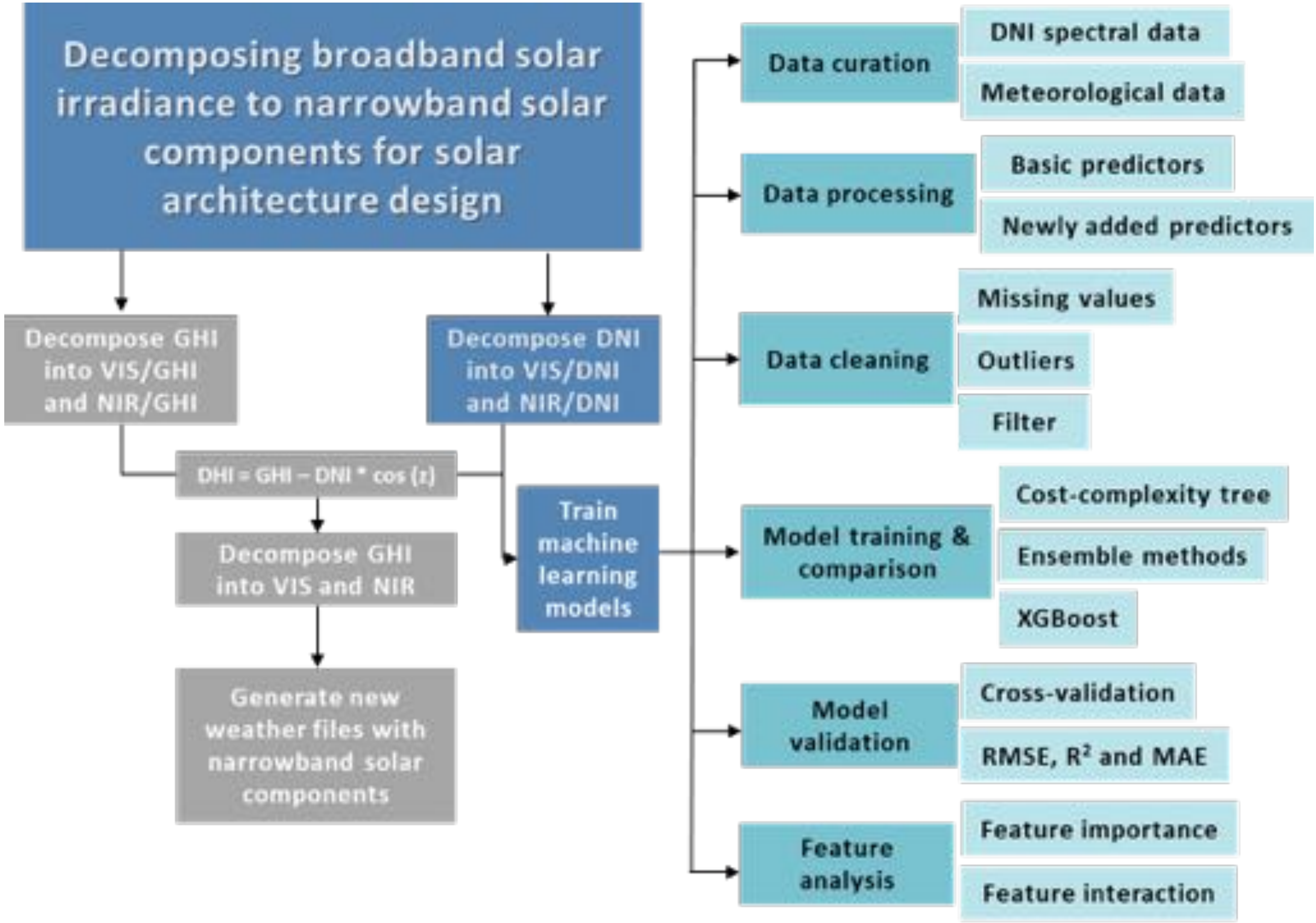
Limitation:
- Local variability
- High cost


**Machine Learning and Neural Network**


Advantage:
- Ability to learn complex patterns
- Reducing the need for physical model
- High Efficiency

Limitation:
- Limited data source
- Hard to interpret
- Hard to generalize

# Methodology



# Methodology

## *Data Collection:*

- Weather dataset: Hourly Meteorological Measurements (HMM)[3] , from Jan 1, 2016, to December 31, 2019
- Solar spectral dataset: Spectral components in GHI collected from outdoor solar spectral data (WISER), in DNI collected from outdoor solar spectral data (PGS-100)[4]
- Other atmospherical parameters: AOD and PWV (GPS-based) from SRRL, NREL[5-6]

## *Data Processing:*

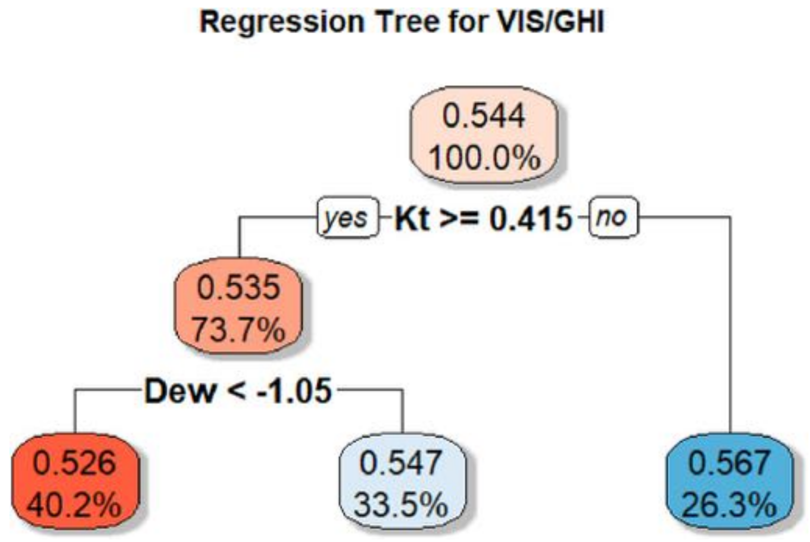
- Basic predictors: GHI, DNI, DHI, cloud coverage, dry-bulb temperature, albedo, dewpoint, relative humidity, wind speed, precipitation, snow, AOD and PWV
- Newly added predictors: Extraterrestrial solar irradiance $I_0$, *Solar zenith angle SZA*, Clearness index $K_t/K_b$, Air mass AM, Cloud transmittance $T_{cld}$
- Targets: VIS (integrated over 400nm – 700nm), NIR (integrated over 700nm – max measurements range) in GHI and DNI

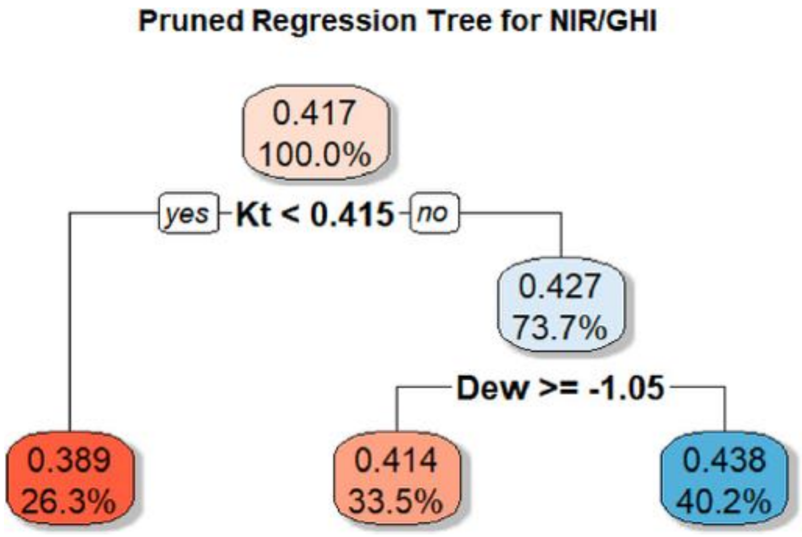
## *Data Cleaning:*

- Criterion: (VIS & NIR > 0) && (VIS/GHI & NIR/GHI & VIS/DNI & NIR/DNI < 1) && (17.5° < SZA < 85.5°) && (VIS+NIR < GHI/DNI), etc..
- Results: There are 35,059 data entries in total. After the data cleaning process, the finalized dataset contains 11434 observations in total

# Results

In our Previous work, we used pruned regression tree to predict the fractions of VIS and NIR components within GHI[7]



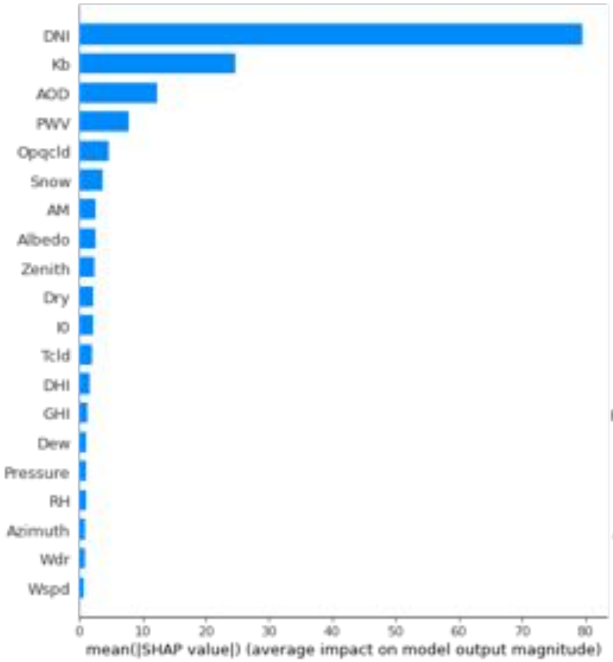
# Results

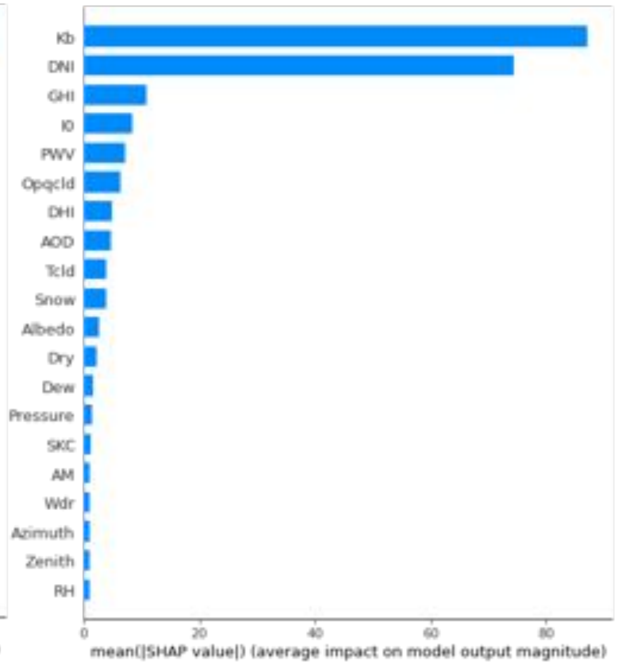
In this work, we compared different machine learning algorithms, and find the best-fit for predicting VIS and NIR value in DNI

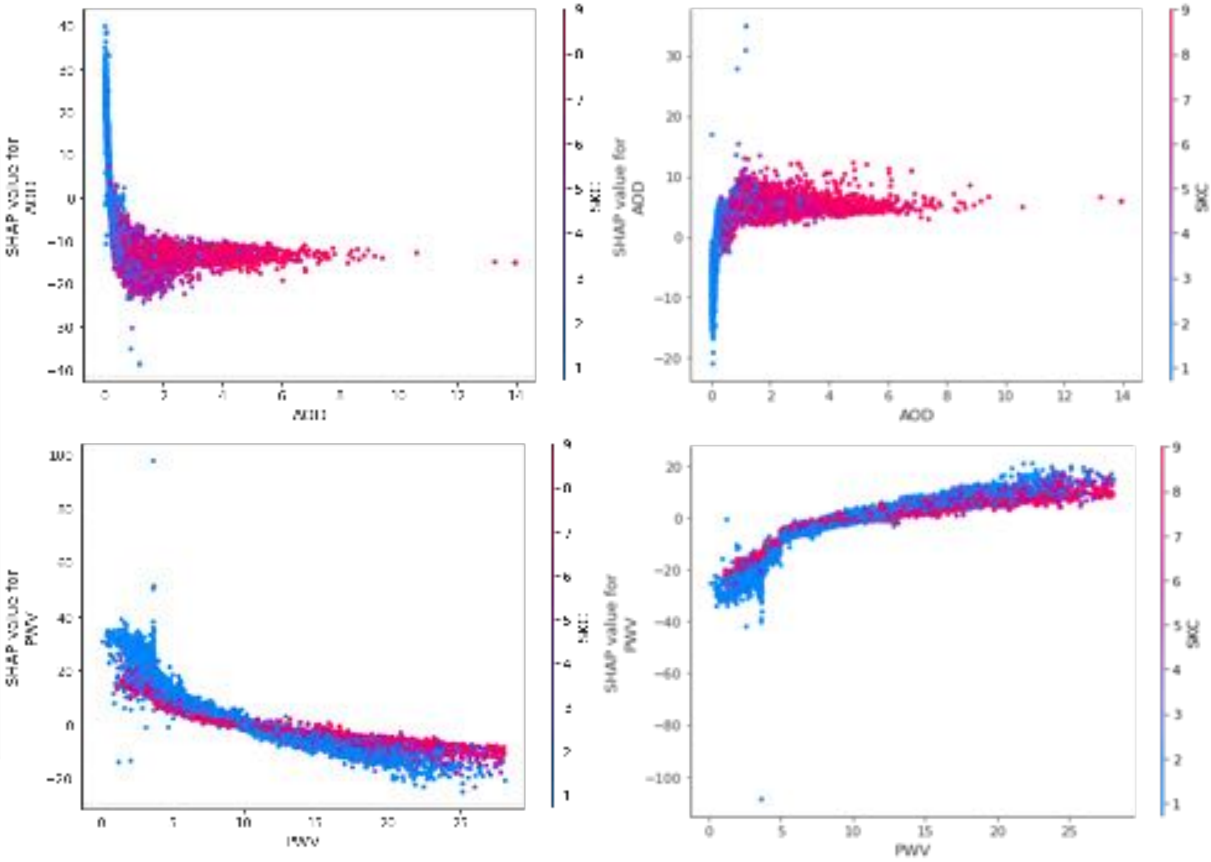
| Model | VIS/DNI | | | | | |
|---|---|---|---|---|---|---|
| | Training | | | Testing | | |
| | RMSE | MAE | $R^2$ | RMSE | MAE | $R^2$ |
| Cost complexity tree | 23.344 | 12.713 | 0.970 | 25.108 | 12.956 | 0.965 |
| M5' tree | 19.272 | 9.725 | 0.980 | 19.916 | 9.690 | 0.978 |
| Random forest | 17.433 | 9.208 | 0.983 | 19.144 | 9.318 | 0.980 |
| XGBoost | 15.698 | 7.718 | 0.986 | 18.280 | 7.989 | 0.981 |
| **Model** | **NIR/DNI** | | | | | |
| | Training | | | Testing | | |
| | RMSE | MAE | $R^2$ | RMSE | MAE | $R^2$ |
| Cost complexity tree | 24.622 | 16.575 | 0.982 | 26.161 | 16.907 | 0.979 |
| M5' tree | 18.719 | 10.105 | 0.989 | 21.342 | 10.6917 | 0.986 |
| Random forest | 17.549 | 9.500 | 0.990 | 19.942 | 9.7087 | 0.988 |
| XGBoost | 15.627 | 7.805 | 0.992 | 18.390 | 8.011 | 0.990 |

# Results

We also tried to study the key features influencing the VIS and NIR within DNI, and these features' inter-correlations

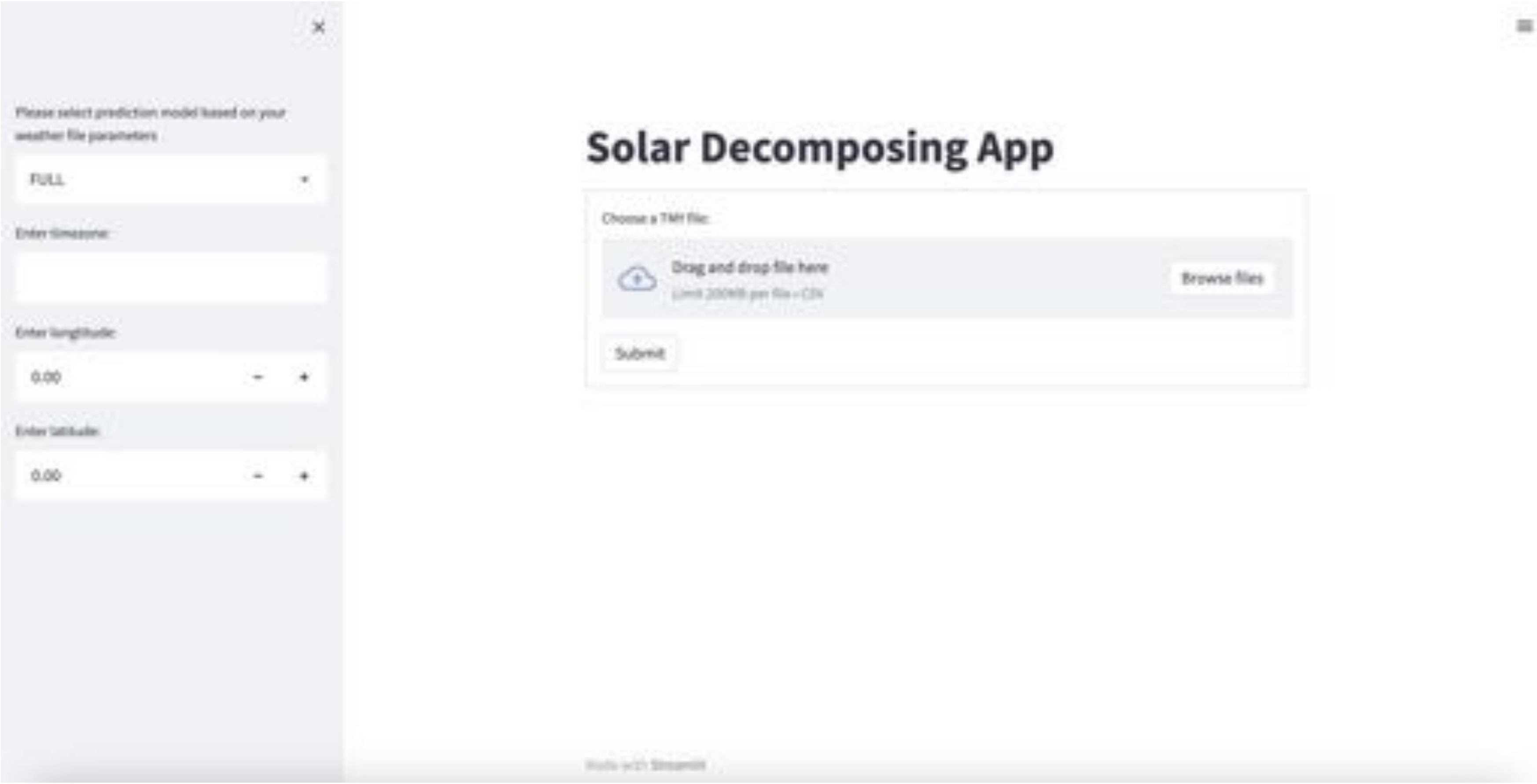


# Application

By integrating our GHI and DNI solar decomposing model, we are trying to build a web portal that could automatically process conventional weather files and turned them narrowband weather files (e.g., VIS/GHI column in replace of GHI column)




Convert .EPW file into .CSV using **EnergyPlus weather file converter**

↓

**Formatting .CSV file's header row** (feature names should be the same)

↓

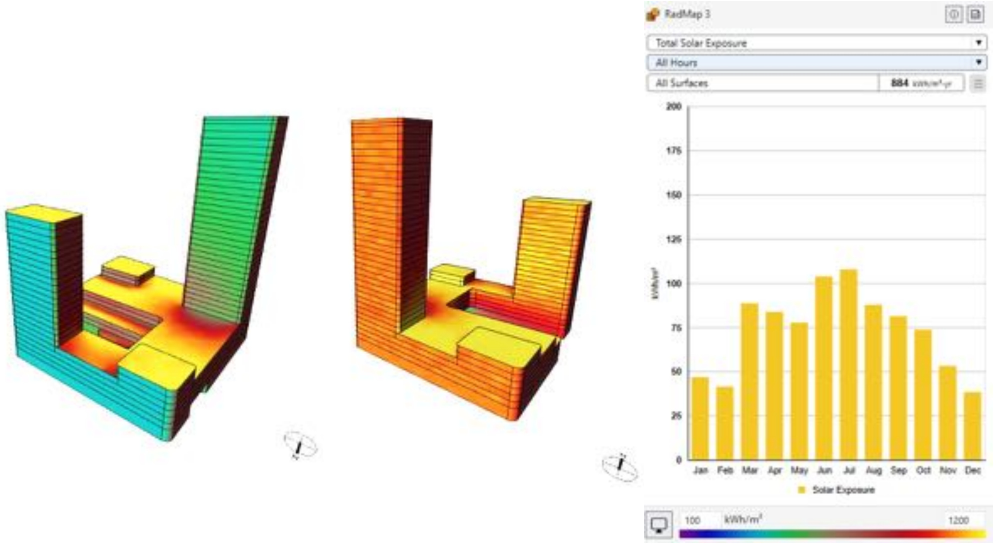
Upload the file to web, **input location details**

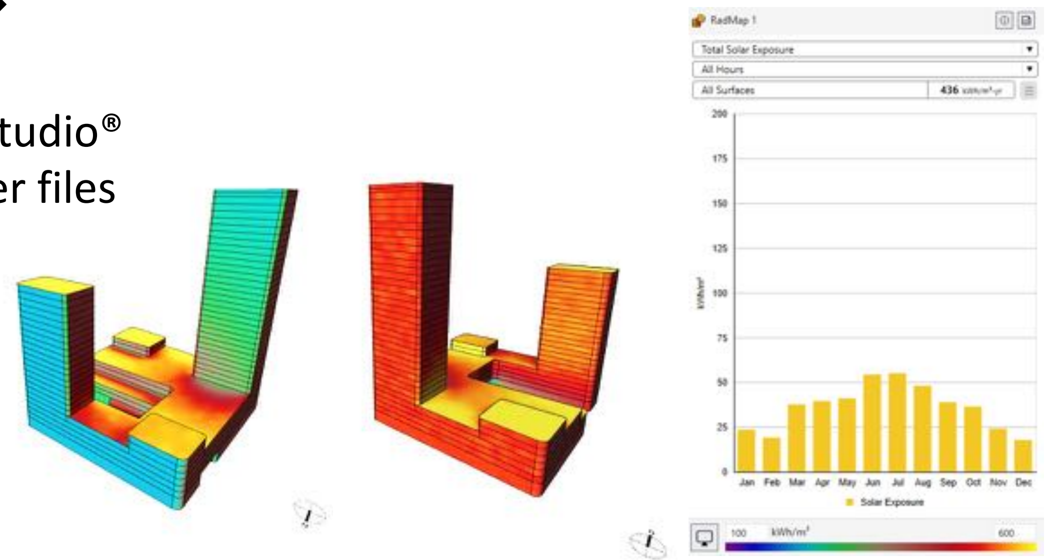
↓

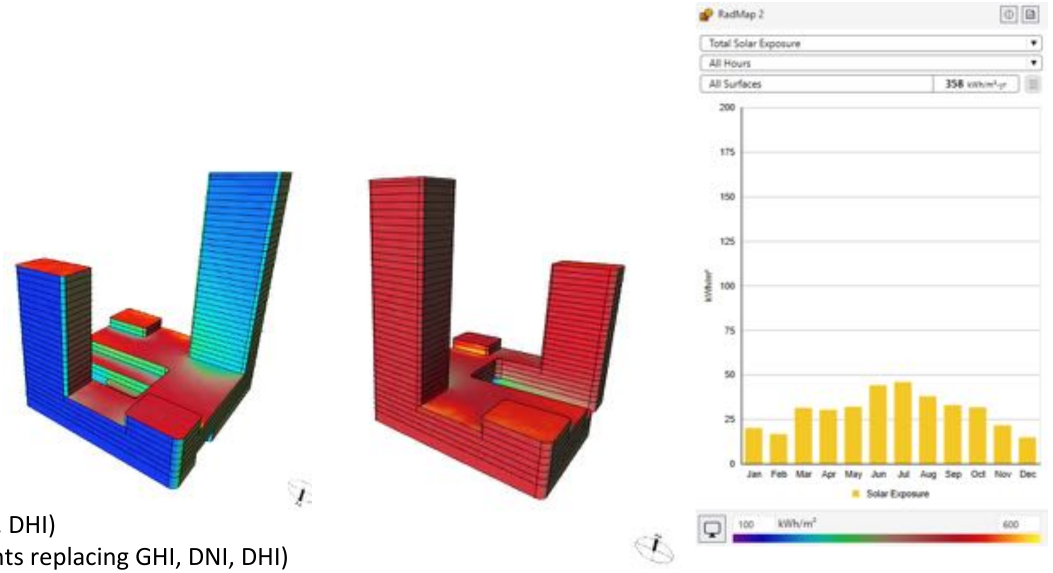
Download handled .CSV file, then use weather file converter again to convert back to .EPW file

# Application

Modified solar analysis for an example building (using ClimateStudio® in Rhino), with newly generated VIS_TMY and NIR_TMY weather files

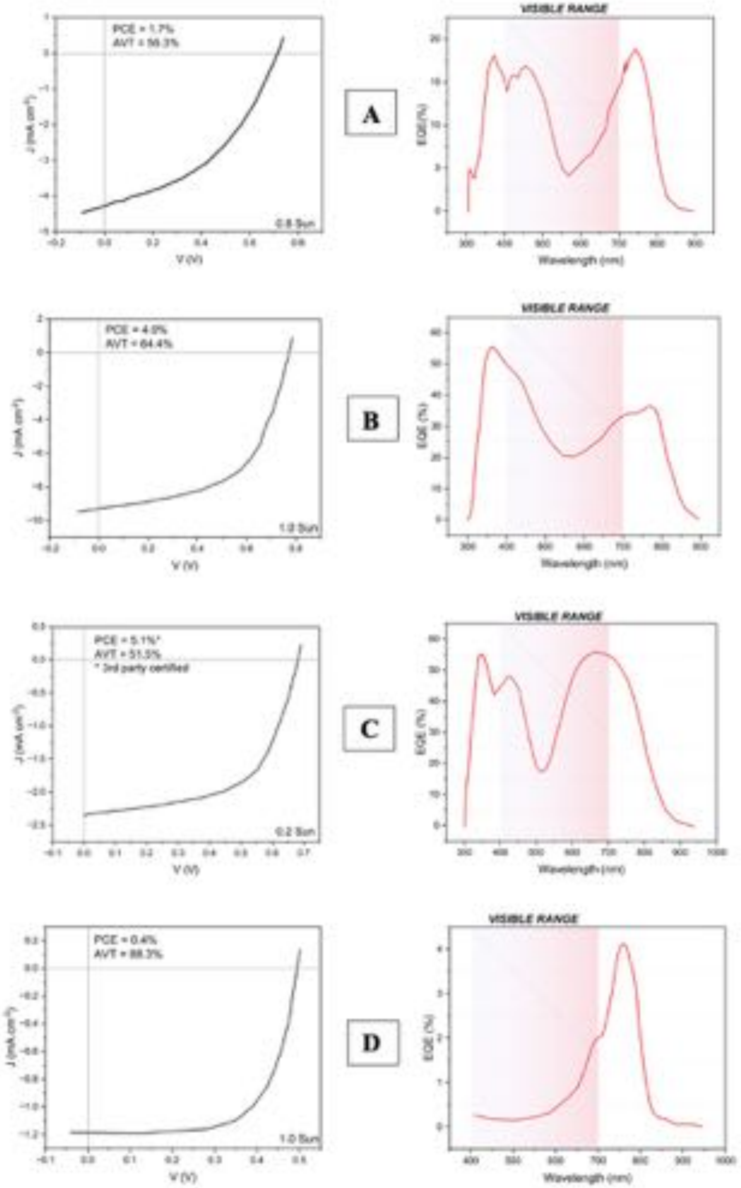



Left: Solar analysis with original weather file (broadband GHI, DNI, DHI)
RightTop: Solar analysis with VIS_TMY weather file (VIS components replacing GHI, DNI, DHI)
RightBottom: Solar analysis with NIR_TMY weather file (NIR components replacing GHI, DNI, DHI)

# Application

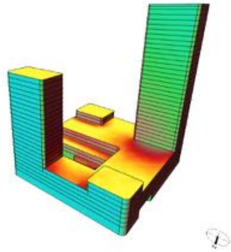



$$J_{sc-range} = \int (EQE(\lambda) * \underline{\emptyset}(\lambda) * q)\, d\lambda$$

$$P_{\text{max-range}} = J_{sc-range} * V_{oc} * FF$$

$$PCE_{range} = P_{\text{max-range}} / P_{in-range}$$

| TPV Device | $PCE_{overall}$ | $PCE_{VIS}$ | $PCE_{NIR}$ |
|---|---|---|---|
| A | 1.7% | 1.9% | 1.4% |
| B | 4.0% | 6.5% | 3.5% |
| C | 5.1% | 7.0% | 4.6% |
| D | 0.4% | 0.28% | 0.58% |



| TPV Device | Output in Broadband kWh/m²-yr | Output in VIS kWh/m²-yr | Output in NIR kWh/m²-yr | Sum (VIS+NIR) kWh/m²-yr | Difference % |
|---|---|---|---|---|---|
| A | 15.011 | 8.284 | 5.012 | 13.296 | 11.4% |
| B | 35.320 | 28.340 | 12.530 | 40.870 | 15.7% |
| C | 45.033 | 30.520 | 16.468 | 46.988 | 4.3% |
| D | 3.532 | 1.221 | 2.076 | 3.297 | 6.7% |

# Reference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# Thank you!