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Retrieving direct and diffuse radiation with the use of sky images

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PERFORMANCE PLUS

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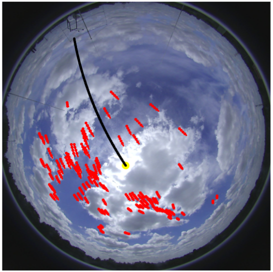
Motivation

Sky Imager based shortest-term solar irradiance forecasts for local solar energy applications



Solar energy applications

- Concentrated solar-thermal (CSP)
- Large grid-connected PV
- Remote area PV with fossil fuel backup
- Energy markets
- ...

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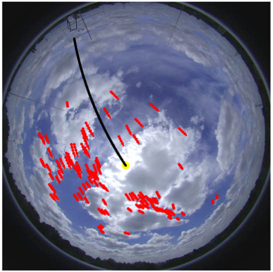

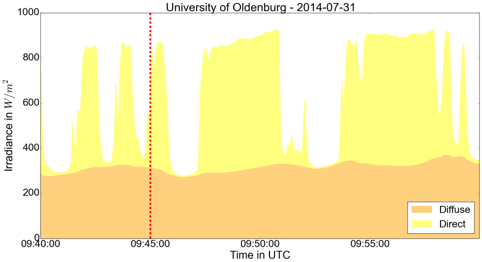

are based on **surface solar irradiance retrieval**

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Background

- **Aim: Retrieve radiation components from image characteristics**
- *Approach:* Use machine learning algorithms with image features and radiation measurements

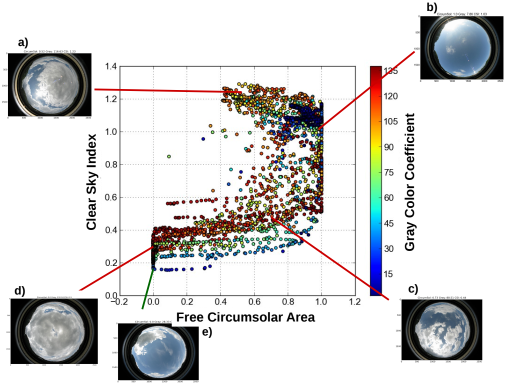

Figure: Sky image features and clear sky index

STSM at Mines ParisTech/EDF R&D, July 2014

Data basis

One year (2014) of sky images and radiation measurements in Oldenburg

- Images every 10 seconds from sunrise to sunset
  (Vivotek FE8174, Total: 1 200 000 images)
- Global and diffuse horizontal radiation
  (Kipp&Zonen CM11, 1s samples)
- Direct normal radiation
  (Eppley NIP, 1s samples)

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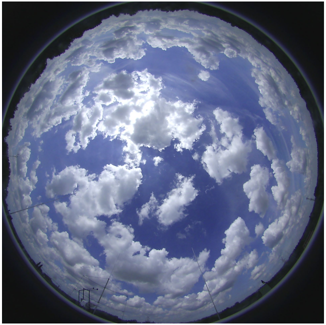
Image features

Choose several global and local image features as input for machine learning



- Texture properties of the Grey Level Co-occurrence Matrix (GLCM)
- Color statistics (RGB space)
- Inter-color relations (e.g. Red-Blue-Ratio)
- Statistics of saturated pixels in circumsolar area in RGB and HSV color space
- Derived features like cloud coverage
- Solar elevation angle
- **Total: 37 possible features**

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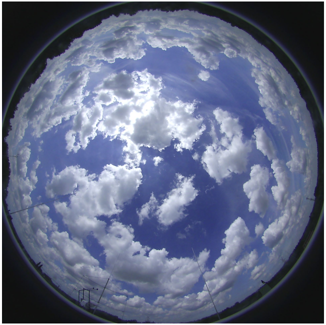

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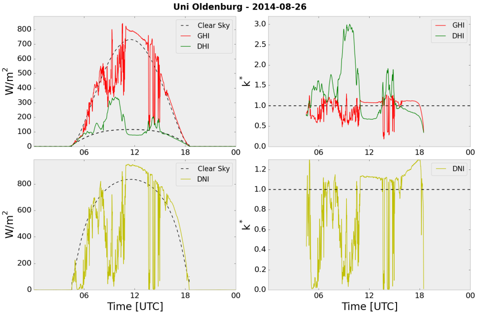
Machine Learning

Task: Train two k nearest neighbour (kNN) models that estimate the clear sky index of diffuse horizontal (k^*_{DHI}) and direct normal (k^*_{DNI}) components.

- $\frac{DHI_{meas}}{DHI_{clear}} = k^*_{DHI} = f(x_0, x_1, x_2, \ldots)$
- $\frac{DNI_{meas}}{DNI_{clear}} = k^*_{DNI} = f(x_0, x_1, x_2, \ldots)$

Strategy:

- Split dataset (70% training + 30% testing)
- Reduce number of features to avoid overfitting and to reduce computation time



Source: www.energiemeteorologie.de -> aktuelle-messungen

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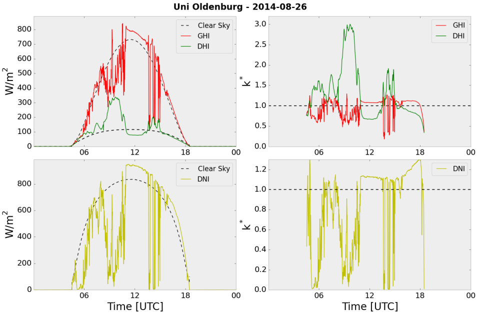

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Feature selection

Reducing number of features

1. Rank features with Decision Tree algorithm
2. Forward selection: Train kNN-model with increasing number of features
3. Validate on independent data set (Criterion: RMSE)
4. Final optimum subset selection is a trade-off between error and computation time

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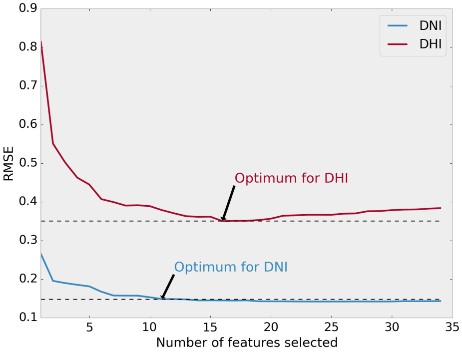

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Feature selection

Selected features with ranking from DecisionTree

Feature Ranking

DNI

1. Average circumsolar pixel intensity (<7°)
2. Red – Blue
3. Gray coefficient
4. Ratio of saturated pixels to all pixels (HSV)
5. Ratio of saturated pixel in circumsolar area (<5°)
6. Contrast
7. Correlation
8. Average circumsolar pixel intensity(<10°)
9. Average circumsolar pixel intensity(<20°)
10. Ratio of saturated pixels to all pixels (RGB)
11. Cloud Coverage

DHI

1. Red – Green
2. Ratio of saturated pixel in circumsolar area (<10°)
3. Average circumsolar pixel intensity (<15°)
4. Correlation
5. Average circumsolar pixel intensity (<20°)
6. Cloud Coverage
7. Ratio of saturated pixels to all pixels (RGB)
8. Number of saturated pixels in circumsolar area (<20°)
9. Mean blue color
10. Contrast
11. Homogenity
12. Skewness Blue
13. Overall Red-Blue-Ratio
14. Dissimilarity
15. cos(SZA)
16. Ratio of saturated pixel in circumsolar area (<10°)

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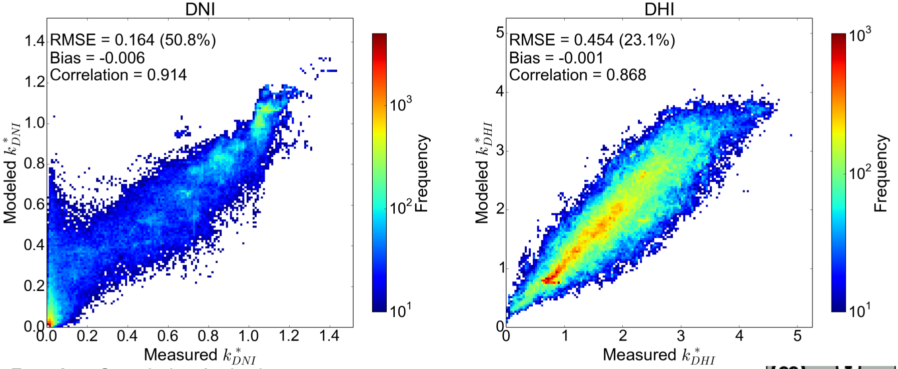
Performance kNN-model

Validation:

test data set: 30% of all data; high-resolution data (instantaneous samples every 10s)



Results: Correlation for both parameters > 0.85

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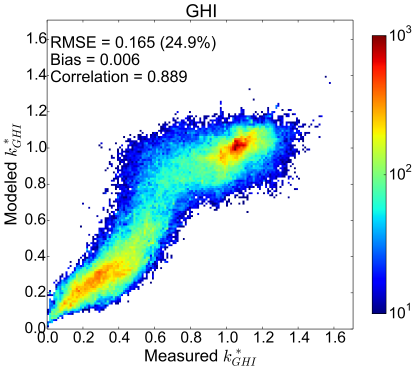
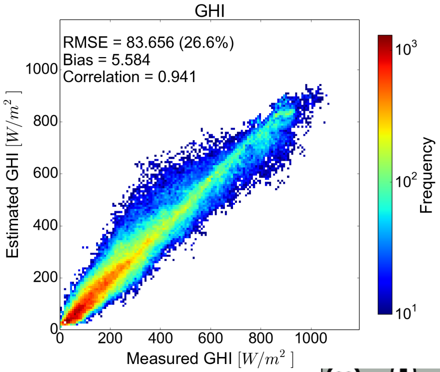
GHI

GHI = DHI + DNI * cos(SZA)

SZA = solar zenith angle





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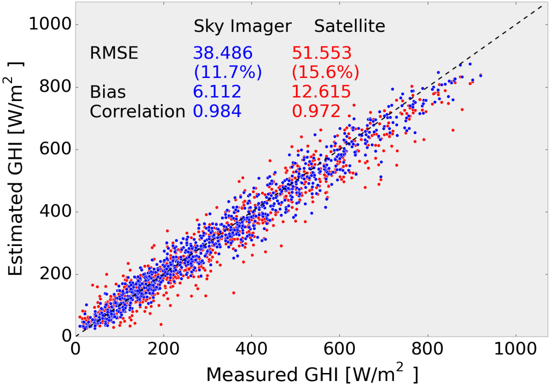
Sky imager vs. satellite retrieval

Global horizontal radiation (GHI)
1-hour average values

- $GHI_{skyimager} = DHI_{model} + DNI_{model} * cos(SZA)$
- $GHI_{satellite}$: retrieved with Heliosat method (*Hammer et al, 2003*) from MSG2 images



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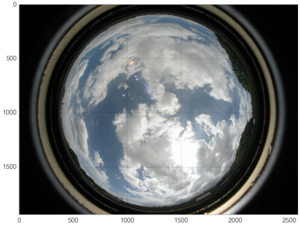
Application

Original Image



Binary cloud map

Sky imager based forecasting

Use modeled diffuse and direct radiation for an advanced mapping of binary information from image to surface irradiance

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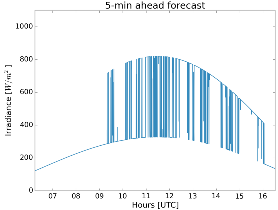
Application

Sky imager based forecasting

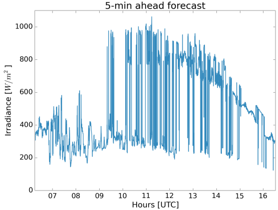
Use modeled diffuse and direct radiation for an advanced mapping of binary information from image to surface irradiance

- **Reference model**: simple mapping of binary pixel information to two clear sky index levels
- **kNN-based model**: more realistic retrieval of current radiation levels

Reference



kNN-modeled



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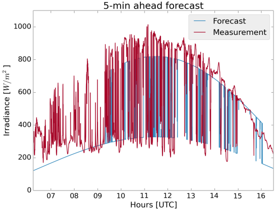

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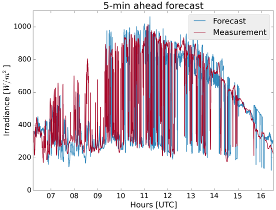

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Summary & Outlook

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- Machine learning useful tool for irradiance retrievals from sky images
- High correlation with measurements for high-resolution instantaneous data
- Lower RMSE than satellite retrievals on hourly average GHI data

Outlook

- Further research on generalization of model for different cameras / camera settings
- Implement model in forecast chain

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Thanks for your attention!

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