Horizon 2020
European Union funding
for Research & Innovation

AIRBORNE AND OPENGEO DATA FOR ENERGY SYSTEM MODEL APPLICATIONS

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Introduction

In order to achieve significant reduction of CO_2 emissions to 80% compared to 1990 by 2050, government agencies and power grid operators support the construction of solar power plants. Therefore, public authorities and electricity grid operators are interested in change detection methods to observe the buildup of renewable energy sources, like private solar module systems or to forecast the electric grid demand and production. To support energy system analyzing applications we extent and/or replace the current used free OpenStreetMap (OSM) data with Earth Observation (EO) detected energy infrastructure sources. First results show an impact of modelling results depending on the level of detail information between free available OSM and EO data.
Building information are generated from 3K OpAiRS data by GIS tools and developed extraction algorithm show a limitation to polycrystalline Photovoltaic module detection. Shadowing effects of PV modules as well as classification of photovoltaic and solar thermal modules from optical airborne data play an important role.

Methods - Input data for GIS-like Energy System Models

Solar modules are built from a combination of different materials and minerals. Therefore, different sensor types were used to collect earth observation (EO) data sets. The study area of Oldenburg and Ulm was recorded with hyperspectral (Ground Sampling Distance (GSD) 1,2m) and optical (GSD 13cm) camera systems (DLR OpAiRS System) in the years 2018 and 2019 over Oldenburg and Ulm region.

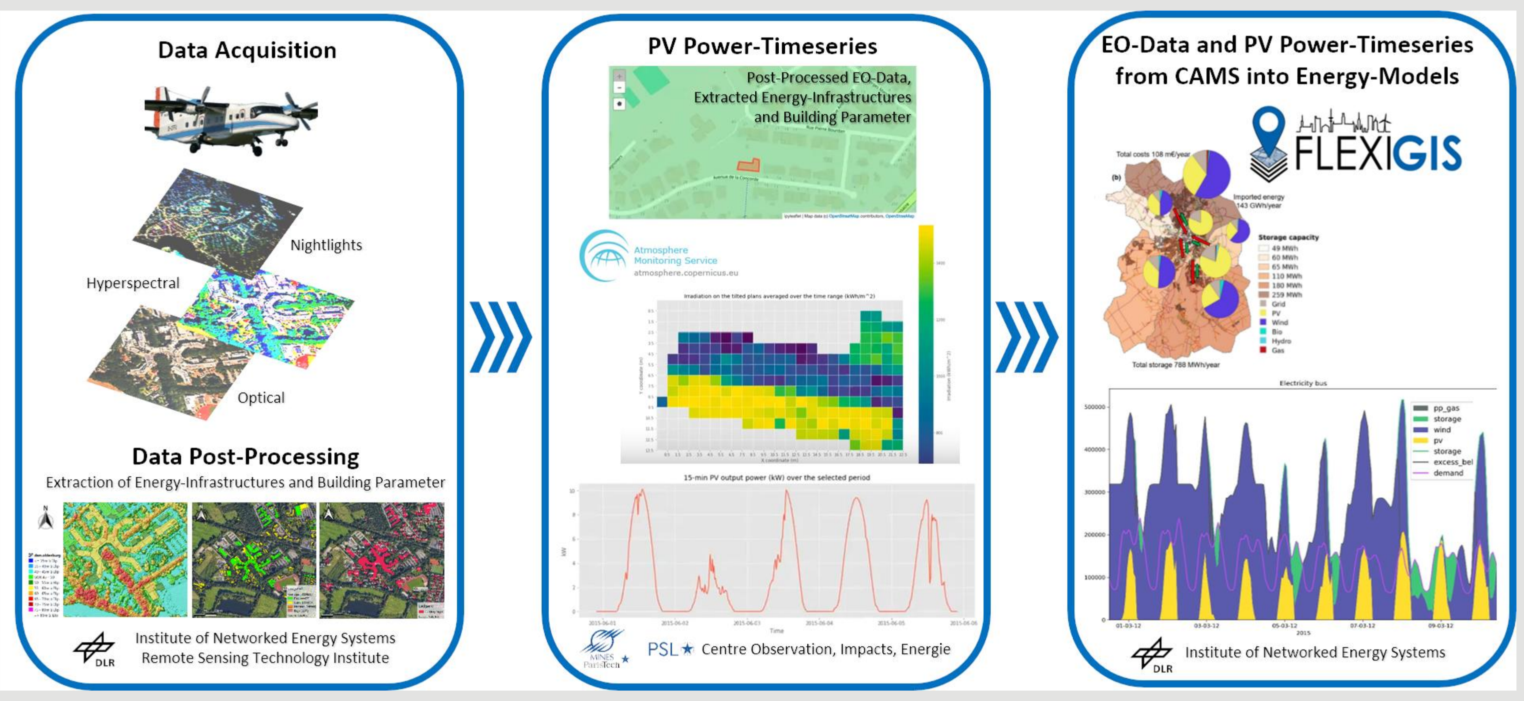

Figure 1: Processing workflow from data collection to implementation in energy system models, example: FlexiGIS. The module in the middle is a cloud-based fast downscaling service using namely CAMS radiation data and high resolution Digital Surface Model developed by MINES Paris - PSL in the framework of the pilot "High PV penetration at urban scale" of the Showcase Renewable Energy of the e-shape.

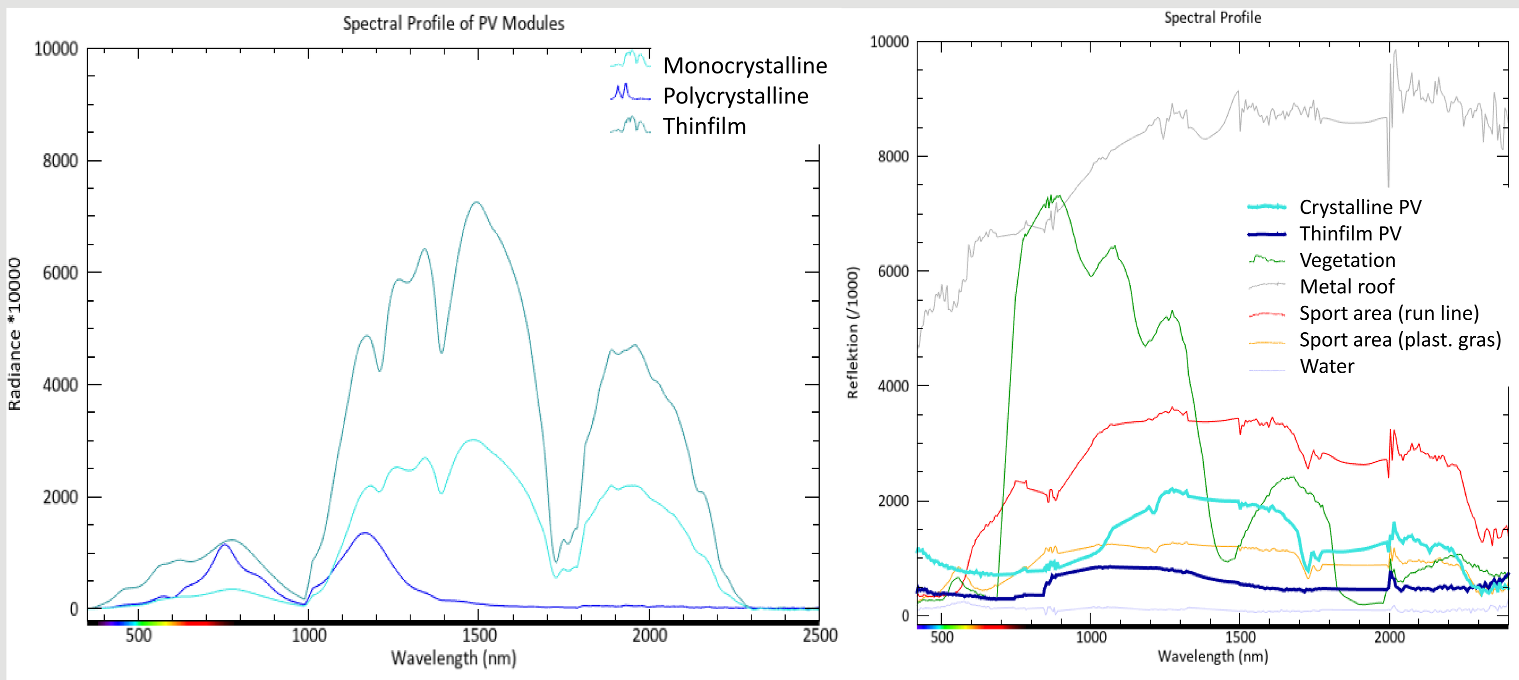

Figure 2: Laboratory spectra from goniometer measurements of mono-, polycrystalline and thin film photovoltaic modules (Gutwinski et al., 2018), as well as characteristic peak information, such as the normalized hydrocarbon index (nHI) (Clark et al., 2003 and 2009) of the ethylene vinyl acetate (EVA) layer of solar modules (Czirjak, 2017), were used to train a spectral indices algorithm for photovoltaic (PV) module detection at Oldenburg region.
Left - laboratory spectra from goniometer measurements of mono-, polycrystalline and thin film photovoltaic modules (Gutwinski et al., 2018); right - extracted spectra from airborne hyperspectral data collection.

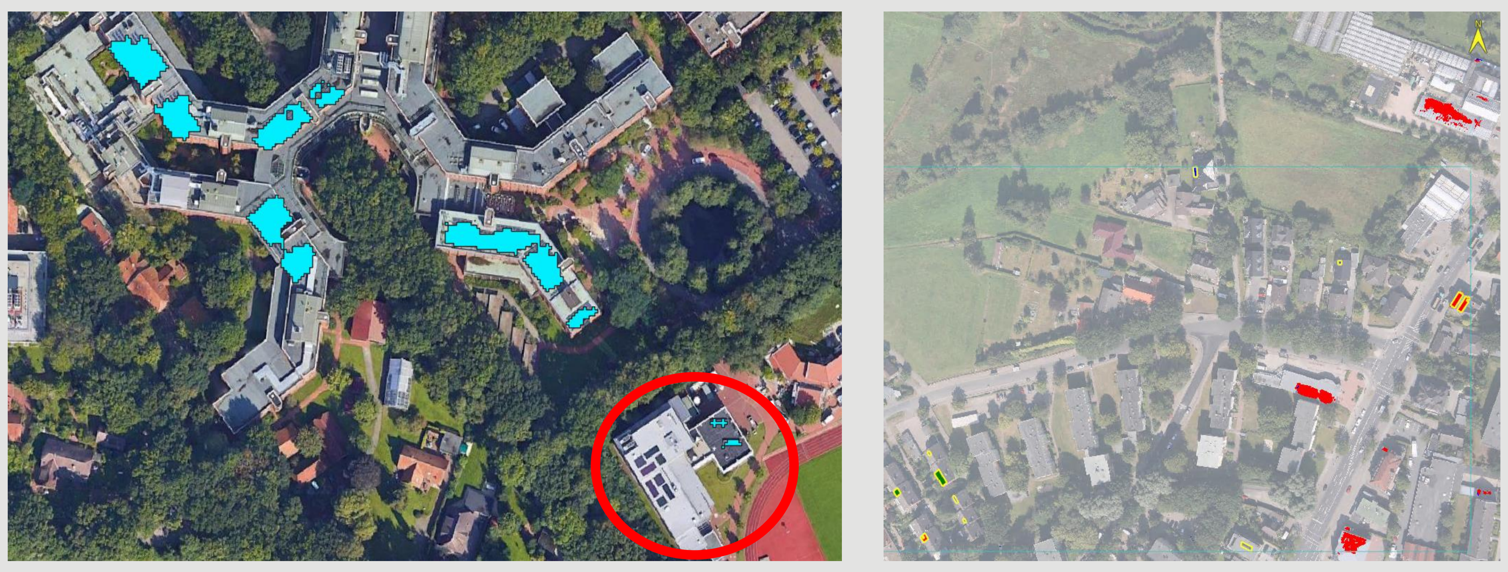

Figure 3: Left: PV extracted over Oldenburg by trained index analysis show validation accuracies up to 90.6% (Ji et al, 2021), but is restricted to mono- and polycrystalline photovoltaic module detection (red circle). A definition of characteristic peaks for thin-film modules detection is ongoing. Right: ENVI Deep learning methods, so-called convolutional neural networks (CNNs), are used for optical data analysis to identify energy infrastructures, such as the detection of photovoltaic modules, and separate them from solar thermal and thin film modules. The actual accuracy of the trained network is at OA = 99,8%, UA = 72,8% and PA = 72,8%. Therefore optimization of the network is ongoing. Color code: red = PV, green = Thinfilm-module, blue = solar thermal, yellow = ground truth/ validation for solar device types.

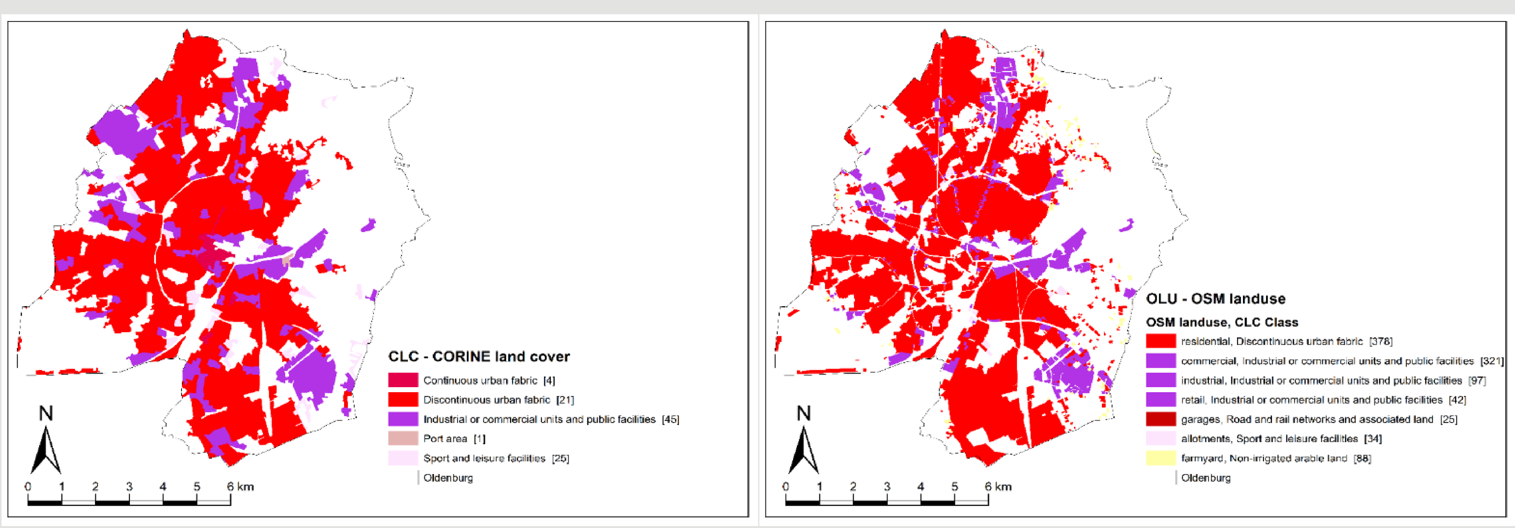

Figure 4: FlexiGIS systematically investigates different scenarios of self-consumption and analyses the characteristics and role of flexibilization technologies in promoting greater self-sufficiency in cities. First tests of Corine Land Cover (CLC) datasets were conducted and compared with the OpenStreetMap (OSM) land use datasets. The coverage, competence and applicability of the datasets for the modeling and application of urban energy systems are primarily investigated. Further tests and examinations are under development. Due to the 5ha processing of the CLC data (Keil et al., 2007), the datasets are not such fine structured like OSM datasets. Existing OSM input data results will be extended to more and more available EO data sets. The OSM based modelling results are compared against EO based energy modelling outputs.

Data usage in Energy Modelling Applications

We are engaged in developing knowledge of PV module construction from PV module research and contribute solar radiation data from the Copernicus Atmosphere Monitoring Service (CAMS) (Schroedter-Homscheidt et al., 2021). The extracted, characterized and geocoded PV and solar thermal systems are used, for example, in self-developed energy modeling software FlexiGIS. The impact on modeling results with EO datasets, in comparison with Open-source input data, is investigated. Irradiance data with a high spatial and temporal resolution are derived using all-sky imagers and can be used to determine the irradiance available to each individual PV installation.

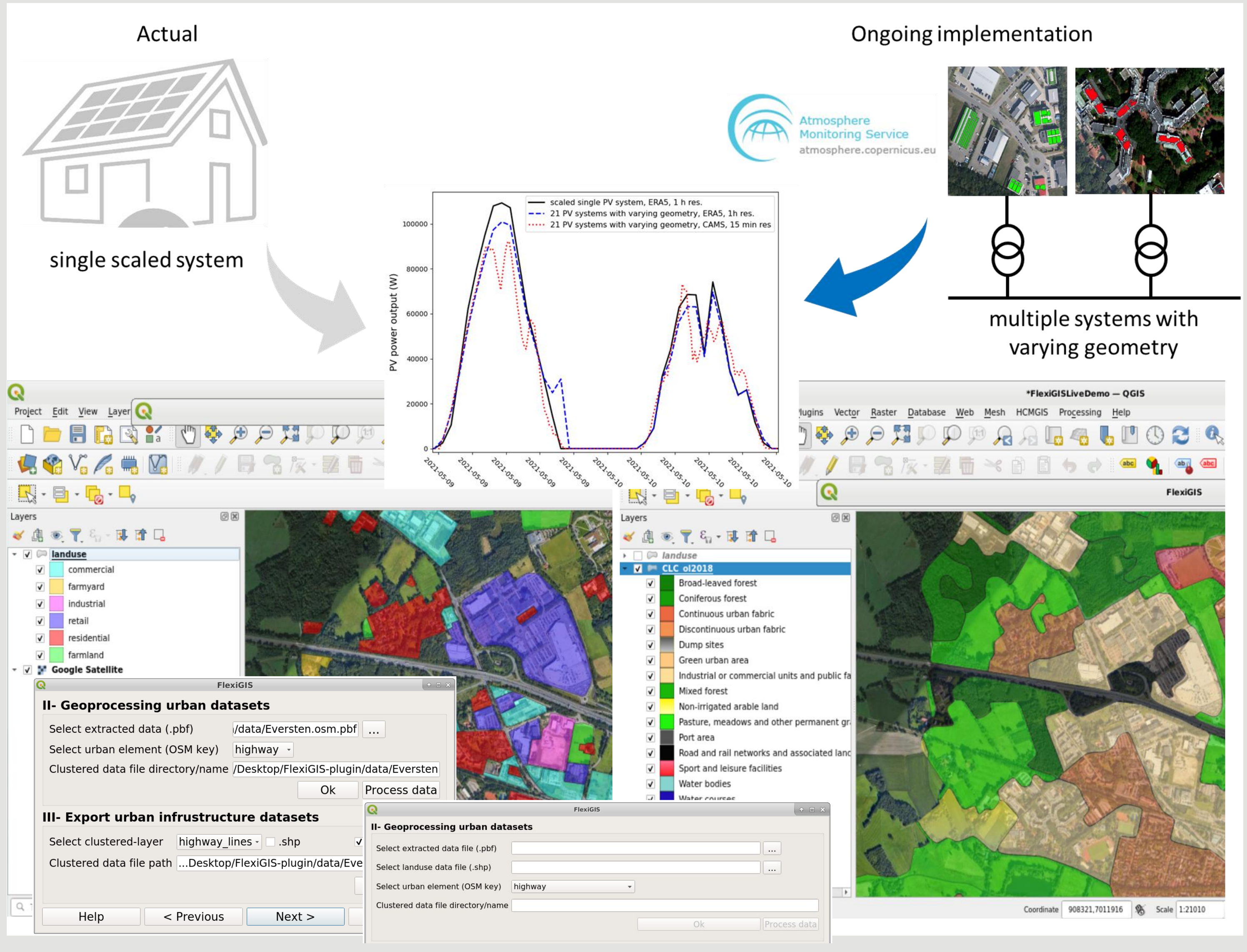

Figure 5: Ongoing activities for EO data implementation into the DLR self-developed energy modeling software FlexiGIS. For data implementation tests a set of 21 fictive roofs with varying geometry are used, to explore the effect of a more realistic roof geometry distribution.

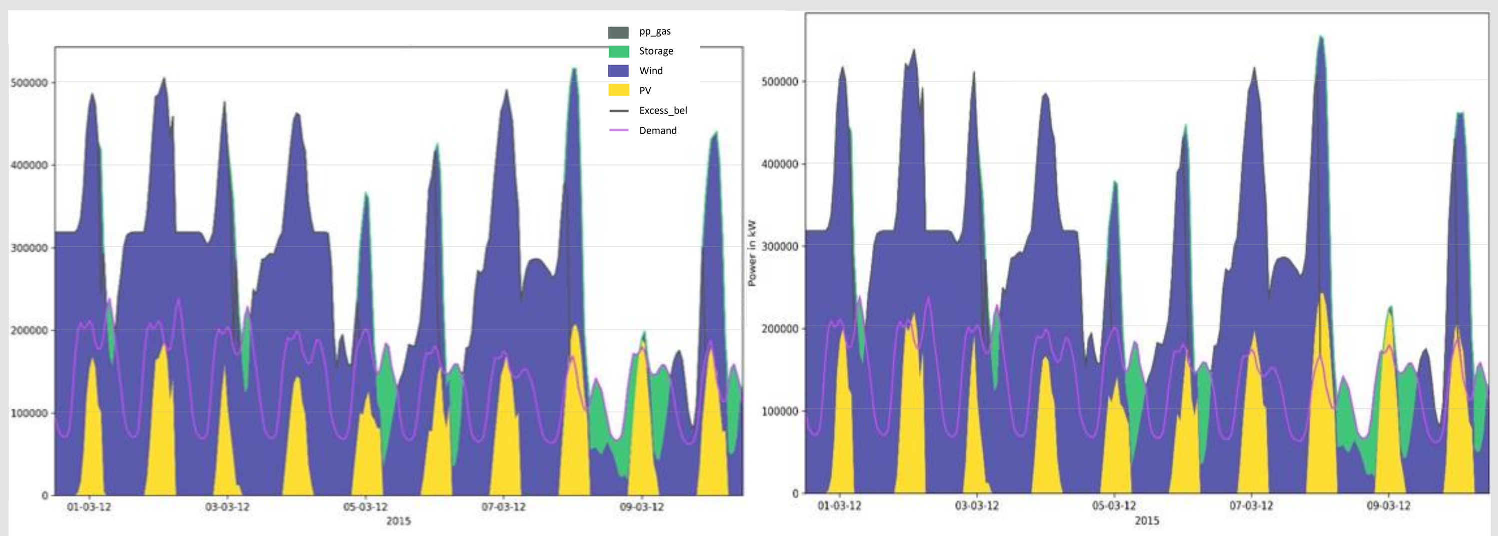

Figure 6 : More realistic roof geometry distribution resulted in a 13% higher storage requirement (right side), despite a better distribution of production during the day.

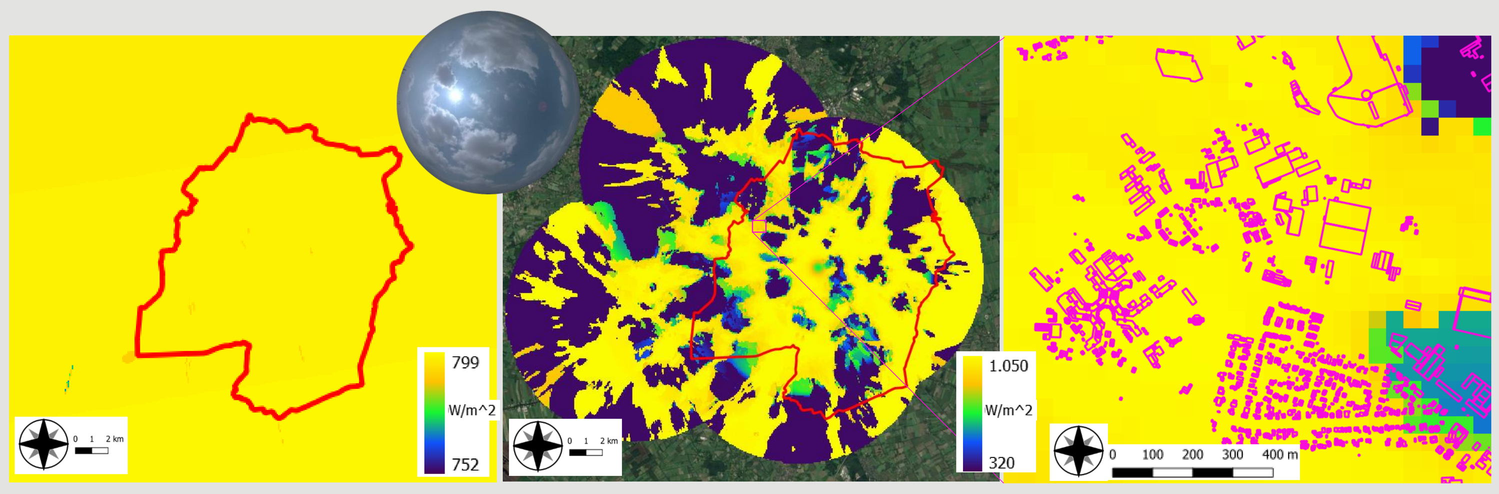

Figure 7: Forecasting systems based on all-sky imagers (ASI), generate irradiance maps with high temporal (30 sec) and spatial resolution (e.g. 5 m x 5 m). Predictions are generated with high accuracy for the next 20 minutes and overall lead times of up to 2 hours. The irradiance maps are used to predict the production of distributed PV installations. A PV model (based on PVLib) provides PV production based on predicted radiation and measurements of temperature and humidity in the urban area. Calculation of the irradiance on the inclined module plane requires accurate information on the shading of individual modules (including partial shading) and on the exact orientation and inclination of each PV installation's modules. Detailed roof information such as building height, inclination and orientation of roof surfaces increase the accuracy and practical applicability of highly resolved forecasts of PV production. Left: ASI forecast in a clear-sky situation; Middle: ASI forecast in a situation with scattered clouds; Right: ASI forecast with clouds and buildings at Oldenburg region.

Conclusion and Acknowledgement

Results based on high-resolution flight data can be further applied to commercial and free satellite data sets such as WorldView, Sentinel-2 and EnMap to enable large-scale, national or even European use. The balance between the loss of information due to the change in spatial resolution of the satellite data and the simultaneous gain of information will be quantified and evaluated with regard to the relevance in energy system models.
The research is funded by the Horizon 2020 e-shape project [European Union's Horizon 2020 research and innovation program, grant no. 820852]. Special thanks to Julian Zeidler for processing the LoD2 data to extract the roof shapefiles and building height information and to Michael Wurm for idea sharing, scientific discussions and knowledge support.

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