# Earth Observation based energy infrastructures to support GIS-like energy system models

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## Motivation and Introduction

Due to increasing worldwide urbanization, increase of urban residents energy demand, decreasing photovoltaic (PV) and solar thermal module prices the number of operating plants has increase significantly in recent years. Authorities and electricity grid operators support solar power plants installations in order to achieve the Federal Government's strategies for reducing CO2 emissions and primary energy consumption by 80% until 2050. For load modelling, generation of demand and production statistics as well as infrastructure design they need up-to-date roof usage and coverage information plus solar plant location data. Many of these systems are not exactly registered and publicly available databases of solar modules are not up to date.

Monitoring strategies of solar plants are interesting for energy forecasting models in research, urban planning and industry. Currently, energy forecasting models are often based on community-based OpenStreetMap data (e.g. Alhamwi et al. 2018). However, these are partly faulty, have insufficient detailed information or have very different regional accuracy. Therefore, we start to collect energy-specific data with Earth observation techniques. Questions of energy system analysis are, for example, the modelling of load profiles in the electricity system.

We focus on energy load quantification in urban areas such as buildings and renewable energy sources detection, photovoltaics and solar thermal energy devices from flight and satellite data.

## Methods and Results - Input data for GIS-like Energy System Models

Solar modules are built from a combination of different materials and minerals. Therefore, ultra-high-resolution airborne optical (Kurz, 2009) and hyperspectral (DLR, 2016) data was collected in the years 2018 and 2019 over Oldenburg and Ulm region (Figure 1). The data sets are collected with the DLR OpAiRS System, mounted at DLR Dornier Airplane and post-processed by DLR Remote Sensing Technology Institute colleagues. Atmospheric and georeferenced correction is done by the ATCOR 4 Processor (Richter et al., 2012).

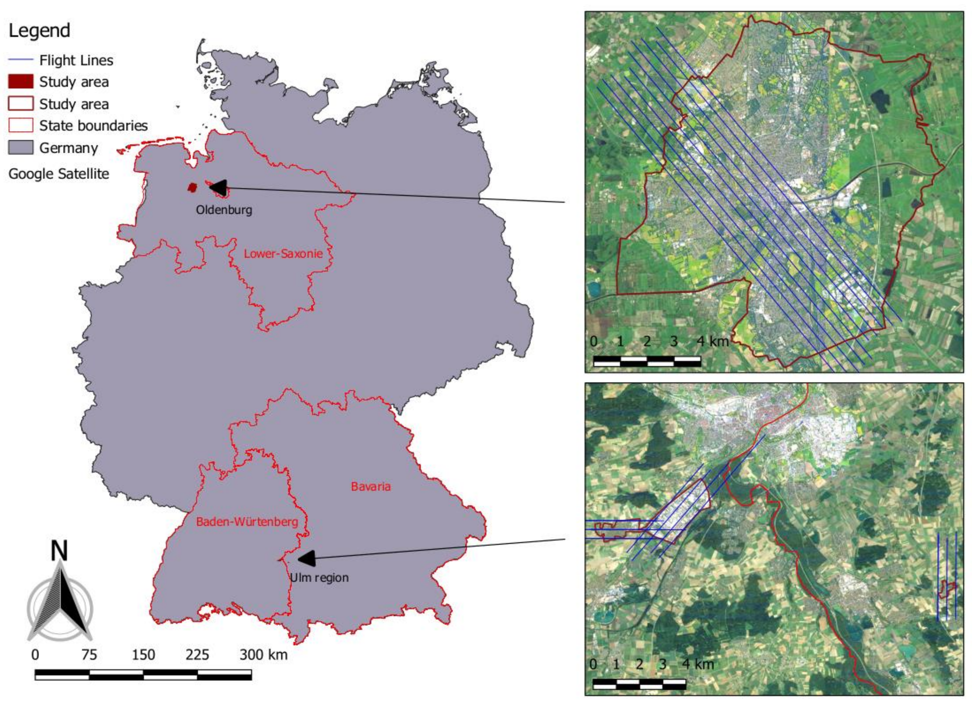


Fig. 1: Study area of Oldenburg and Ulm with flight lines of the hyperspectral (GSD 1,2m) and optical (GSD 13cm) data collected by the DLR OpAiRS System

Deep learning methods, so-called convolutional neural networks (CNNs), implemented in the ENVI software 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 (Figure 2). 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.

Fig. 2: Classified raster by trained pixel segmentation network; red = PV, green = Thinfilmmodule, blue = solar thermal, yellow = ground truth/ validation for solar device types

Laboratory spectra from goniometer measurements of mono-, polycrystalline and thin film photovoltaic modules (Gutwinski et al., 2018) (Figure 3), as well as characteristic peak investigation, 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 (Figure 4).

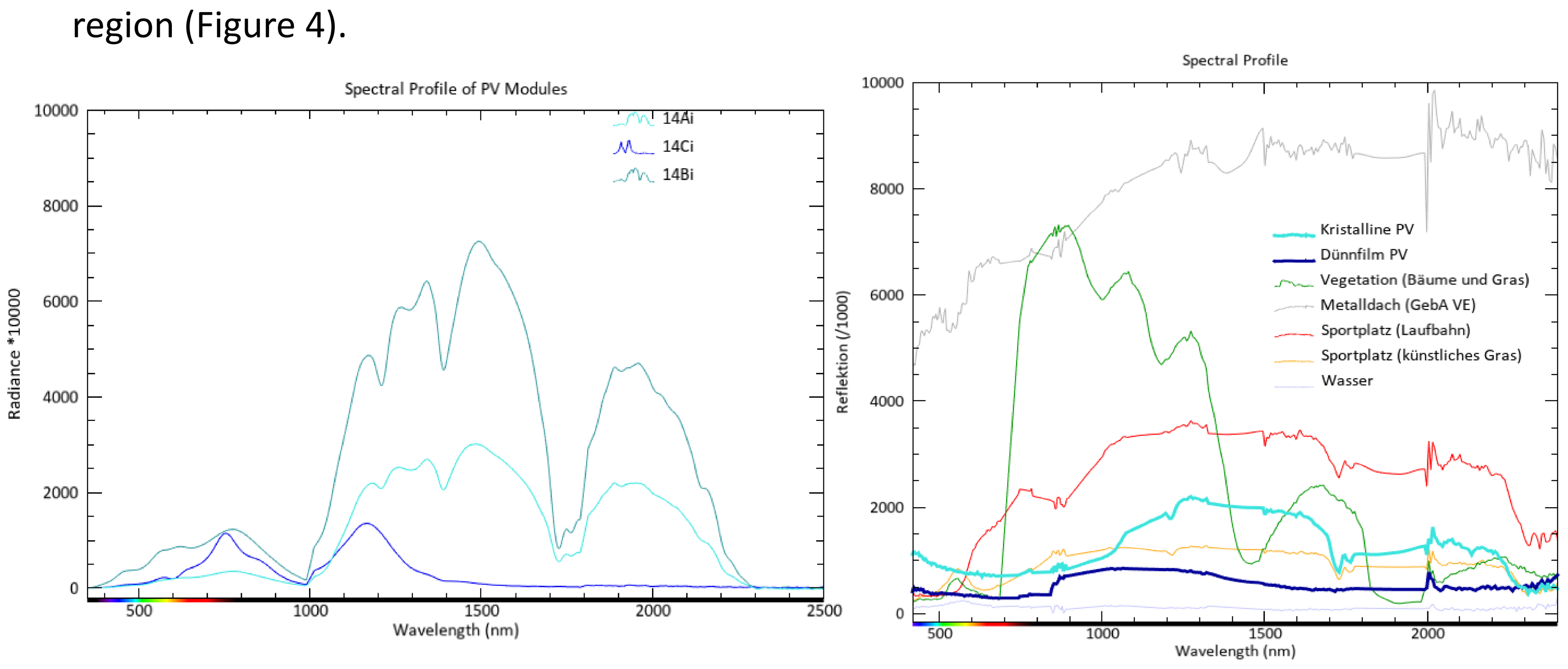


Fig. 3: left - laboratory spectra from goniometer measurements of mono-, polycrystalline and thin film photovoltaic modules (Gutwinski et al., 2018); right - extracted spectra from airborne hyperspectral data collection.

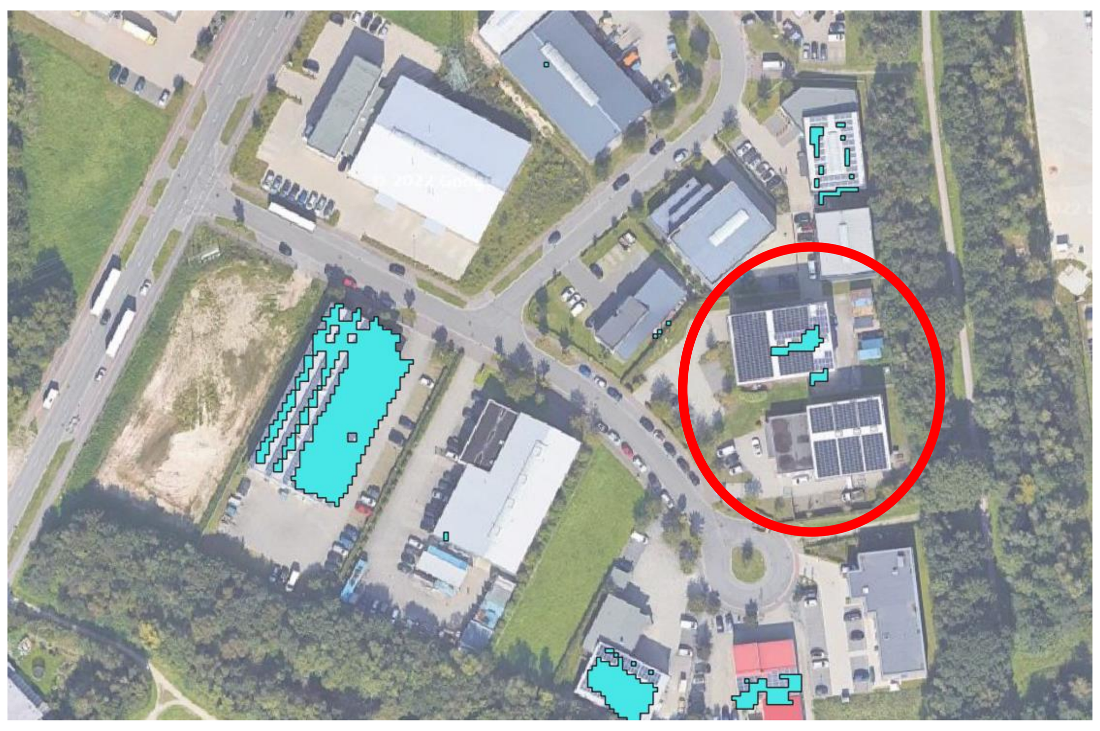

Fig. 4: PV extracted over Oldenburg by trained index analysis show validation accuracies up to 90.6% (Ji et al, 2021), but is restricted to mono- and polycrystalline photovoltaic module detection (red circle). A definition of characteristic peaks for thin-film modules detection is ongoing

Based on optical flight data an ultra-high-resolution digital surface model was generated and combined with open LGLN LoD2 data to extract building height, angle and orientation of roof surfaces at Oldenburg region (Figure 5).

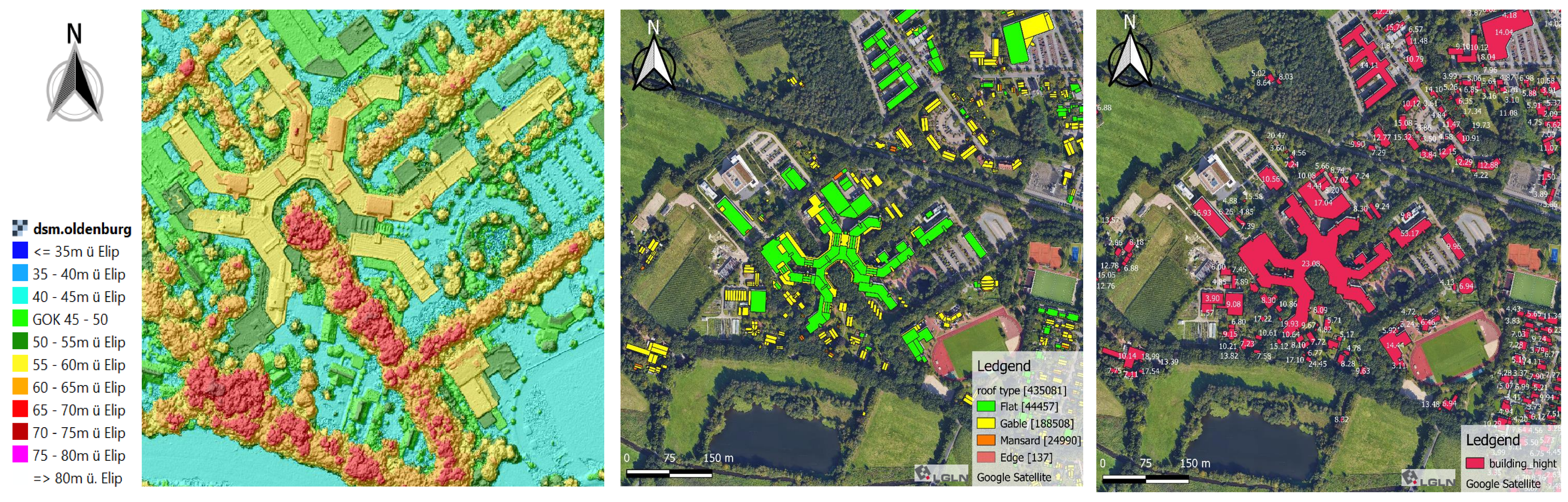


Fig. 5: Wechloy University area at Oldenburg; Left: ultra-high-resolution DSM from optical airborne data; Middle: roof top types; Right: building heights

At the institute, we have detailed 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 (Figure 6). The impact on modeling results with EO datasets, in comparison with OpenStreetMap input data, is investigated.

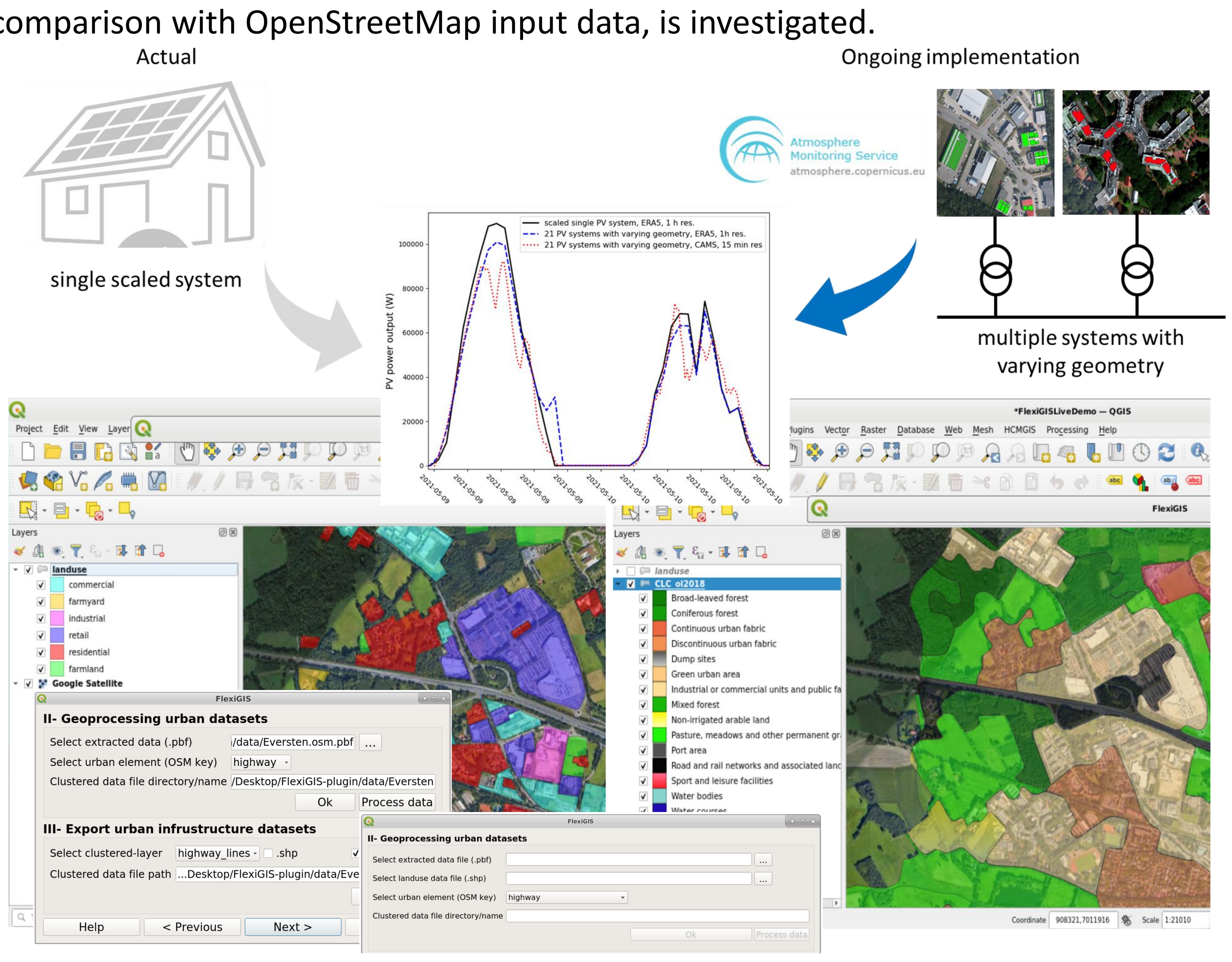


Fig. 6: Ongoing activities for EO data implementation into the DLR self-developed energy modeling software FlexiGIS

## 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 is quantified and evaluated with regard to the relevance in energy system models.

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