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Solar PV Maps for Estimation and Forecasting of Distributed Solar Generation

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Tackling Climate Change with Machine Learning

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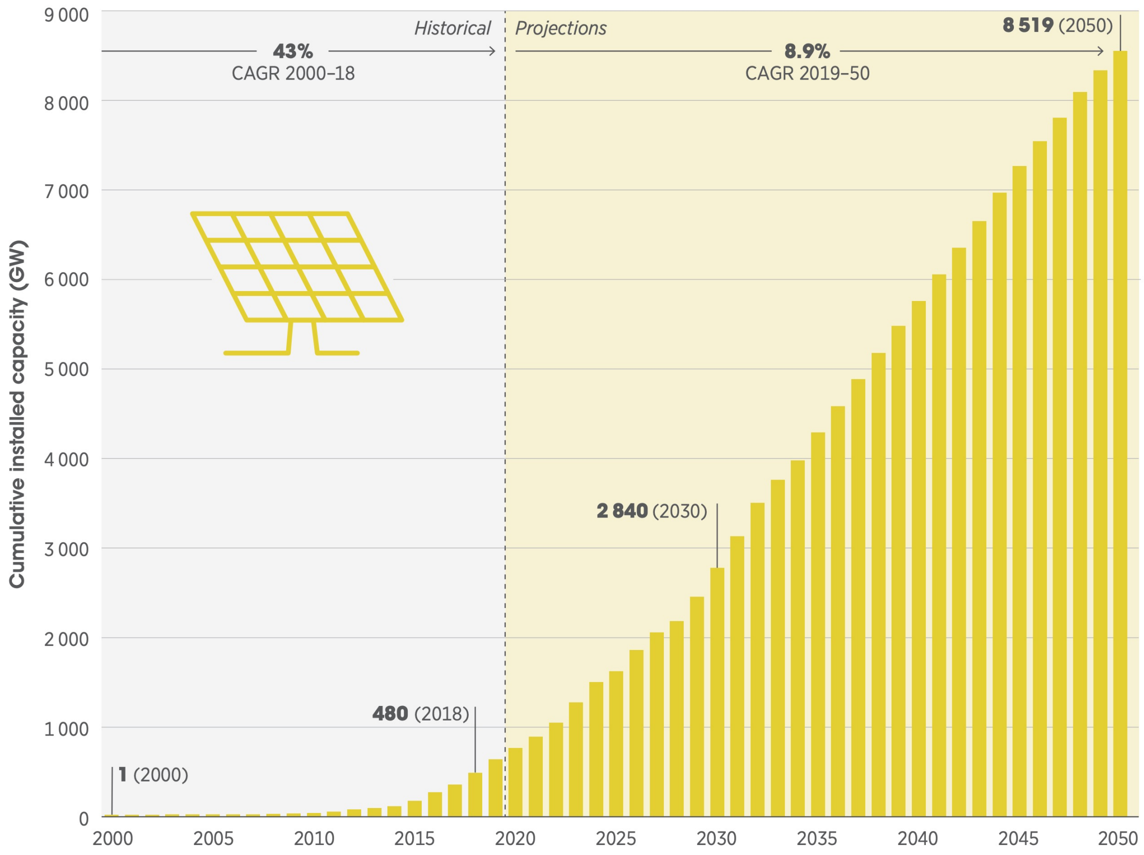
Image credit: https://bit.ly/3gXD43i

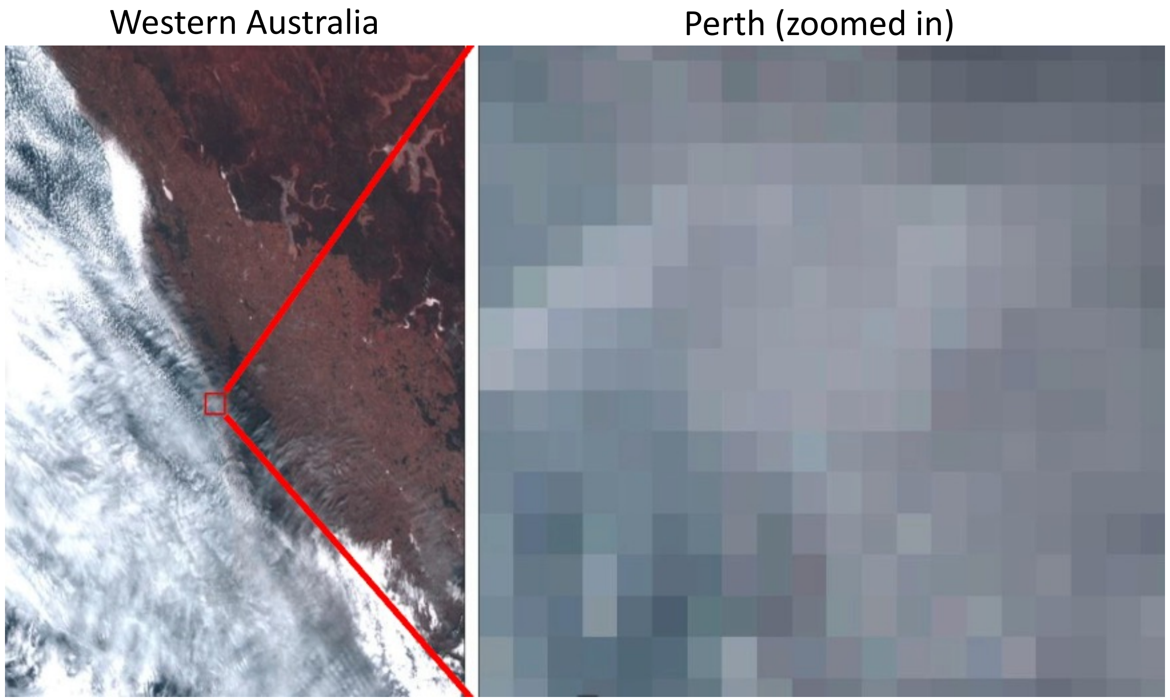
Distributed Solar PV: Bright Future, but also Challenges



Source: International Renewable Energy Agency (IRENA), 2019 – link

- Solar PV is the world's fastest growing form of energy generation
- From 2019 to 2024, the number of solar rooftop systems on homes is set to more than double to >100 million
- However, too much solar PV can cause many problems, especially at the distribution level:
  - Entire neighbourhoods can start to act as generators
  - Significant system volatility and instability
  - Market instability
- If we don't address these issues there is a risk that the full value of distributed solar PV won't be realised.
- Many of these problems can be addressed with **better forecasts of distributed solar PV**
- These forecasts must typically be for a whole region – such as the entire area connected to a substation in the grid

Solar PV Forecasting: Geospatial vs. Point Source Data



Consider the neighbourhood in the right figure – almost every house has rooftop solar PV.
How can we forecast solar power output of the whole neighbourhood in the next 3-6 hours?

A common approach in solar PV forecasting is to use geospatial data, such as weather data or satellite imagery.
An example is shown in the figure on the left: Himawari satellite data, having a resolution of 1km x 1km.

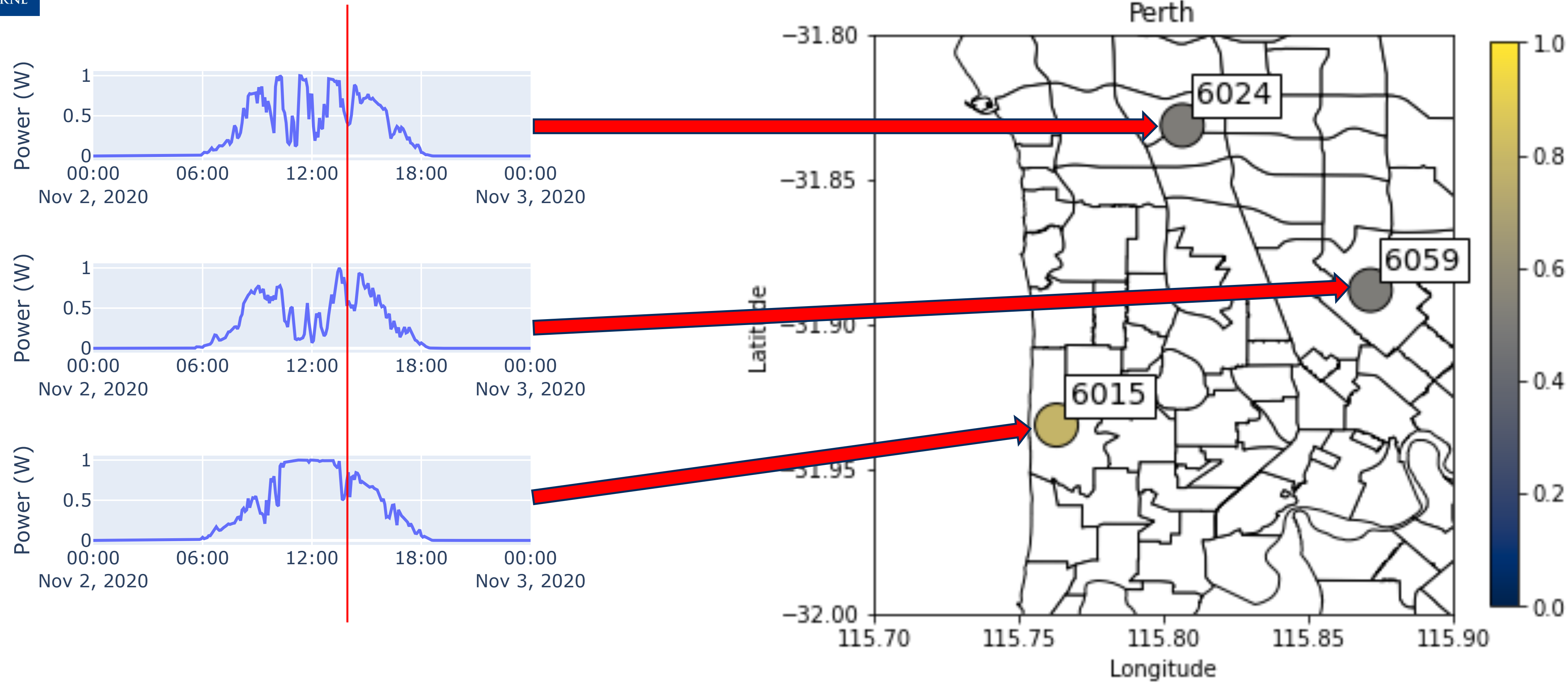
Such data can be very useful, but it is still often low-resolution, may have a lag, or may not properly take local conditions into account.

Solar PV Forecasting: Geospatial vs. Point Source Data

However, we have much more than just geospatial data available.
There are many other sources of data that we can leverage, such as time series data collected directly from the solar PV systems.

The above figures show three examples of daily solar PV time series data.
(Note that these were not actually retrieved from the houses in the right figure).

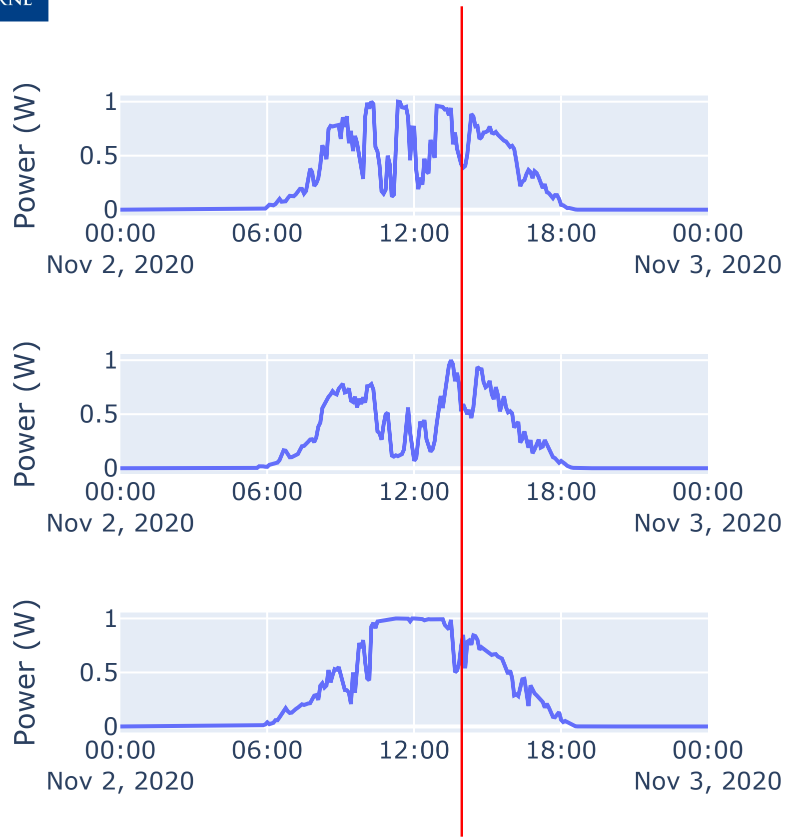
Generating “Solar PV Maps”

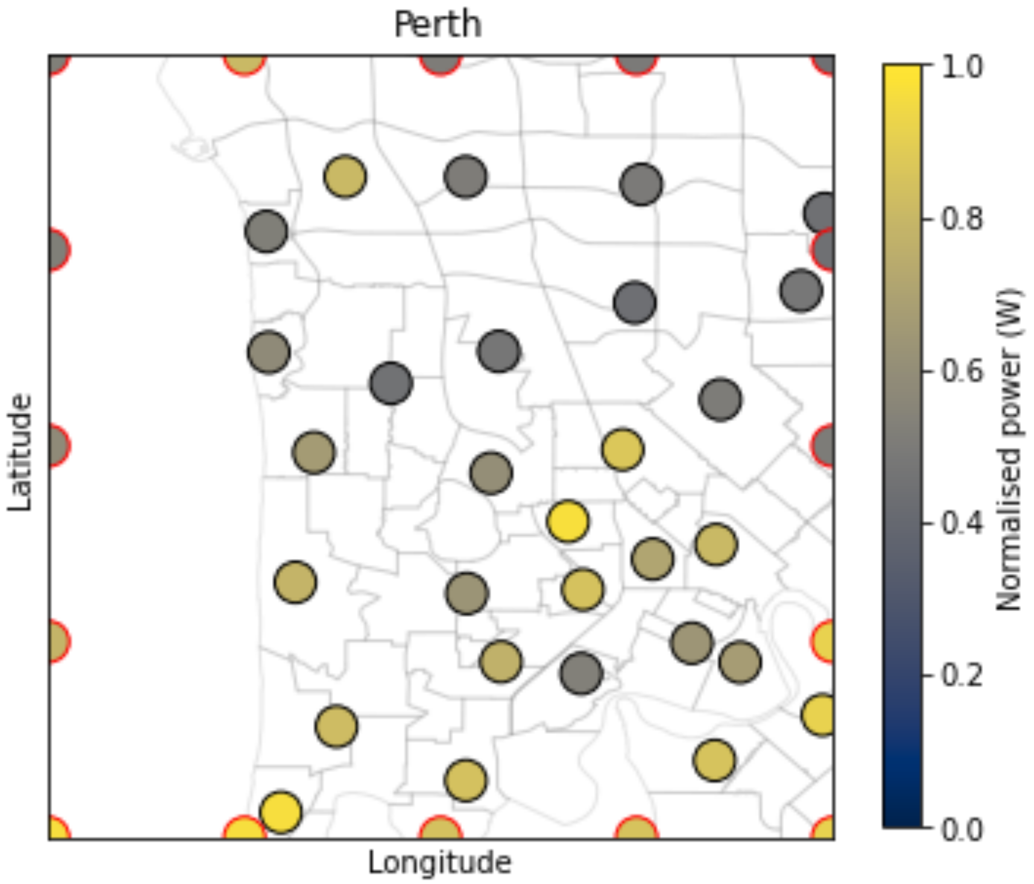


How can we combine time series data collected from individual points with geospatial data that covers an area?

At any point in time, the current value for each of these time series can be mapped to a specific geospatial location (in this case, postcode centers). Here we use coloured circles to represent the value, but in principle these represent simple float values in the range [0, 1].

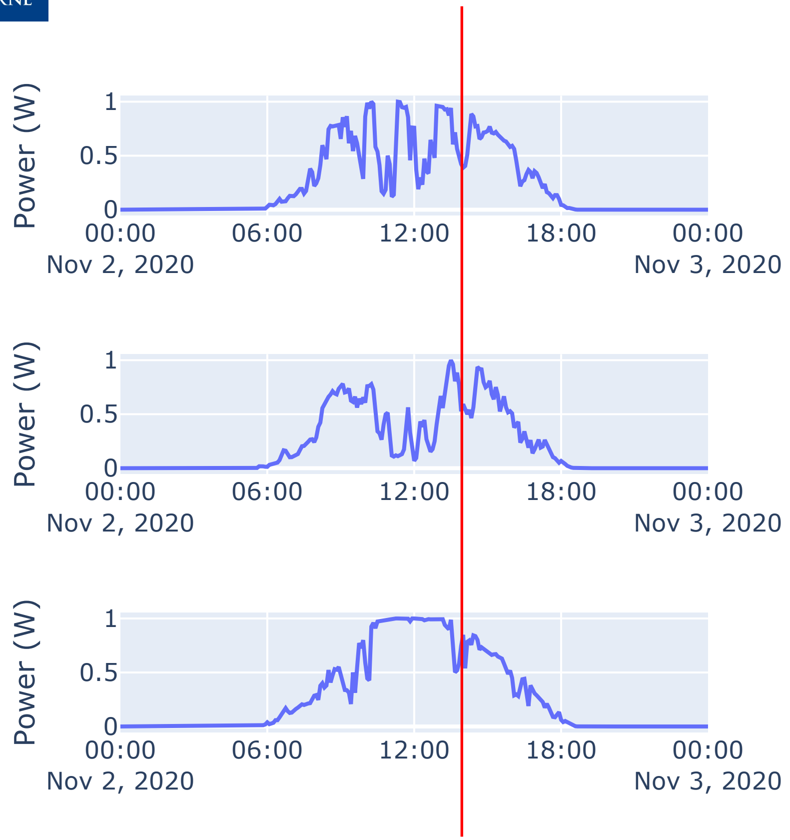
Generating “Solar PV Maps”

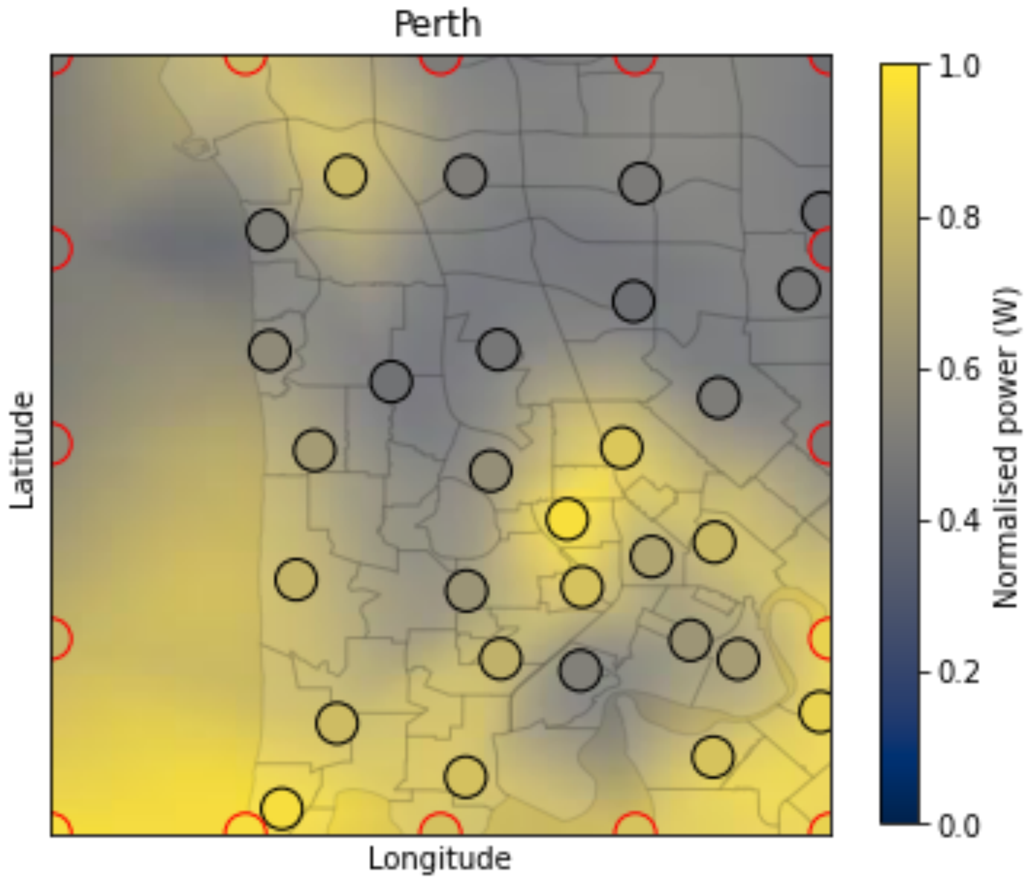




We can expand our set of points with more data sources, and estimate boundary conditions (in this case using the same value as the nearest point).

Generating “Solar PV Maps”

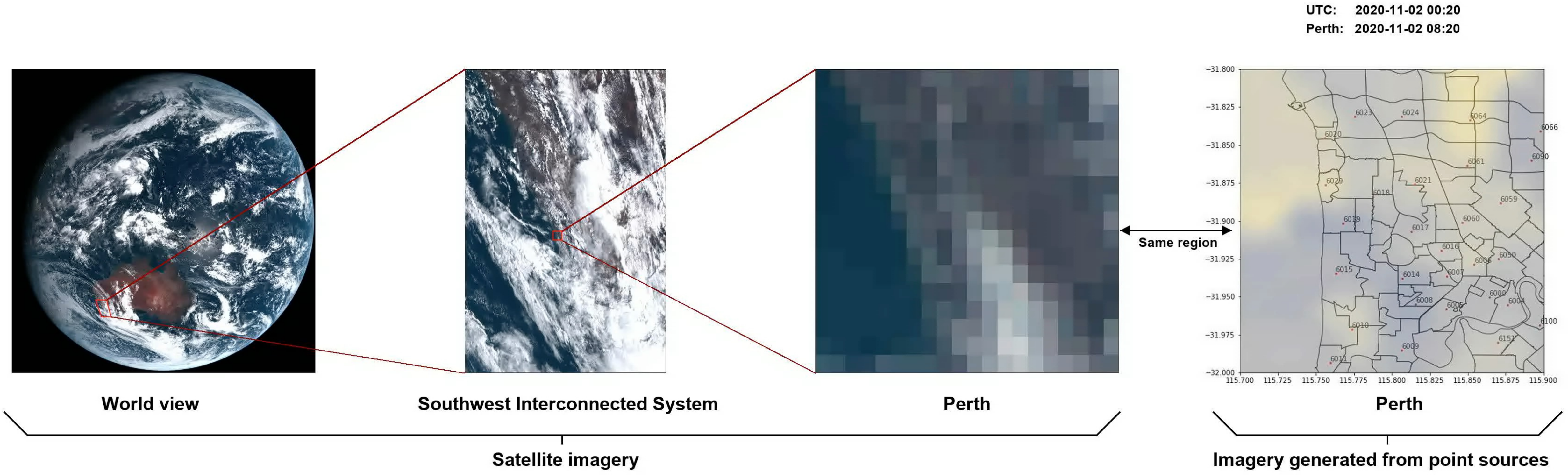




We can then fit a surface to these points that covers the entire area. In this case, we are using a piecewise cubic, continuously differentiable, and approximately curvature-minimizing polynomial surface (available within scipy).

This gives us, for every interval, an approximation of solar PV power for any location in the map, at any resolution we choose.

Comparing Satellite Images with Solar PV Maps



The above video shows a side-by-side comparison of satellite imagery (left three images, at increasing levels of zoom) and our solar maps.

There is a reasonable level of correlation (compare white in satellite images with dark blue/grey in solar maps). For a more thorough validation, please see the paper accompanying this presentation.

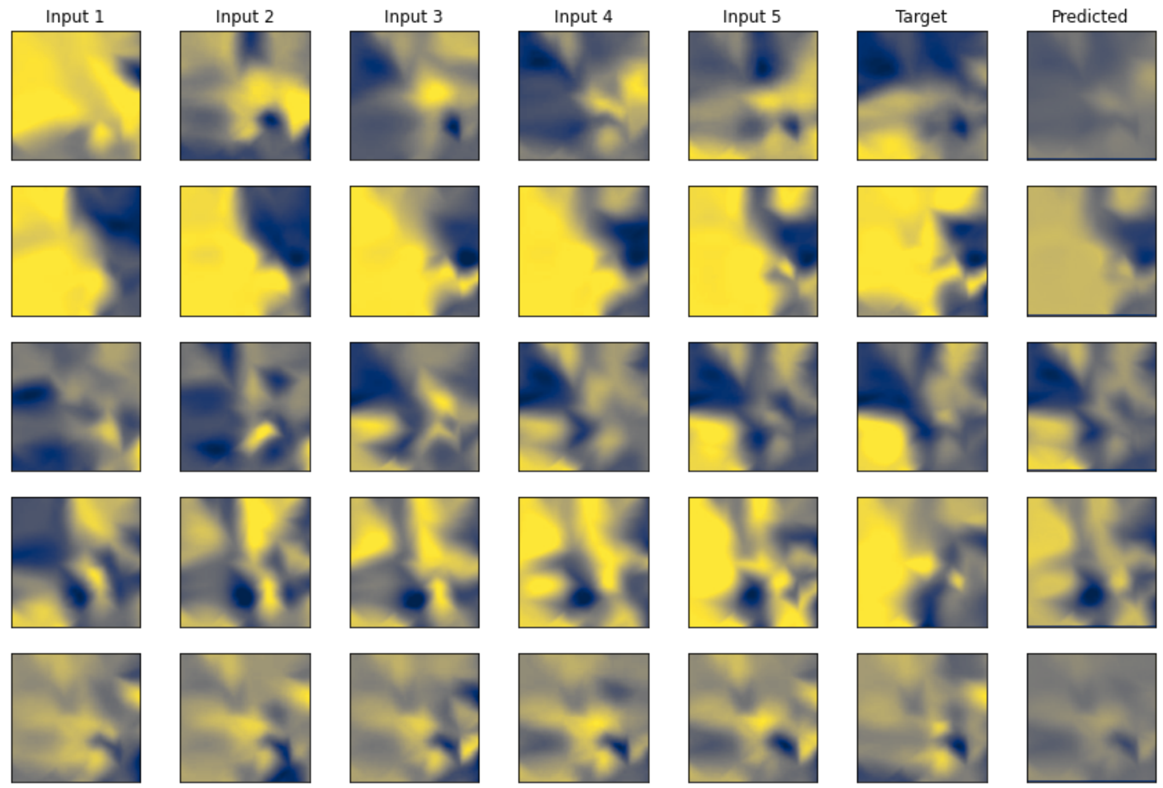
However, the solar maps are actually generated from measured power values, and can be created to have any desired resolution.

The potential value of these Solar PV Maps

This remains early work, and validation, testing and development is ongoing.

However, we consider there to be significant potential value in this approach:

- Improved accuracy using ground-based data sources
- Continuous surface fitting means high resolution – better than best available satellite imagery
- Deep–learning based forecasting for entire regions (see example at right)
- Potential to forecast locations for which we have no data
- Correlation with satellite imagery – could be used to better understand value of different spectra, or for satellite image super-resolution.
  -> This could have implications not just for solar PV, but also for other sectors (such as agriculture)



An example of how solar maps can be used in a deep learning framework. Each row represents a sample, where five consecutive solar maps form the input and the subsequent solar map is the target. Even with the use of a simple network, good predictions can be obtained.

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Thank you!

We are grateful to **Solar Analytics** for providing anonymised solar power generation data, and to **NCI Australia** for access to historical satellite imagery.

We look forward to continuing the discussion with you:

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Image credit: https://bit.ly/3gXD43i