News & views

Energy infrastructure

Solar-panel detection goes global

Lynn H. Kaack

An inventory of the world's solar-panel installations has been produced with the help of machine learning, revealing many more than had previously been recorded. The results will inform efforts to meet global targets for solar-energy use. **See p.604**

Many governments do not maintain a central database listing the size and locations of their country's photovoltaic systems — installations of solar cells that generate electricity. Remote-sensing approaches using machine-learning techniques have the potential to collect these data by detecting such facilities in satellite images. On page 604, Kruitwagen *et al.*[1] show how machine learning can be used to mine imagery of the entire globe to produce an inventory of commercial-, industrial- and utility-scale solar installations. The authors locate more than 68,000 such facilities, many of which were not on record.

Solar panels come in various sizes and can be placed on the ground, on top of structures or even on water. They can therefore be used as a distributed energy resource — that is, at relatively small scales, close to where electricity is needed. This also makes it difficult to keep track of photovoltaic installations. However, researchers, government agencies, grid operators and other stakeholders need detailed information about these distributed resources if they are to plan land use, monitor the adoption of photovoltaic technology and integrate it into the power grid. Policymakers also need to consider the equity of solar energy: are some people more able to take advantage of its benefits than others[2]?

I often use photovoltaic installations as an example to show my students how surprisingly poor data availability is for some topics that are central to climate policy. In the United States, for example, the most comprehensive database of photovoltaic installations[3] covers only around 80% of installations. Collection of these data is expensive and often impeded by regulatory or institutional barriers — which is why approaches based on remote sensing and machine learning offer a practical alternative.

Machine-learning approaches for identifying photovoltaic installations in high-resolution aerial and satellite imagery have grown at an impressive speed. The method was first proposed[4–6] in 2016 — for example, as a way of finding residential installations in an area of 135 square kilometres across Fresno, California[4]. Only two years later, machine learning was used to scan satellite images of the entire continental United States for solar arrays[7], providing the first complete picture of residential installations in that country. Around the same time, utility-scale photovoltaic installations were also mapped for Japan[6,8] and China[9]. Kruitwagen *et al.* now report another leap for the technique, with their analysis of 72.1 million square kilometres of Earth's surface to detect commercial-, industrial- and utility-scale photovoltaic installations around the world.

Kruitwagen and colleagues' study is a milestone because it shows that machine-learning approaches can be used to catalogue global energy infrastructure. It also highlights the considerable challenges involved in doing so. For instance, the global scope comes with differences in data quality and availability, and an immensely diverse set of imagery that demands a considerable quantity of manually annotated data to train the machine-learning system. At that scale, huge computational resources are also needed to process the vast number of images. The authors tackled these challenges with creativity and with the ample patience required for the hand-labelling. They used two different sources of satellite imagery, and set up a process involving several 'deep learning' models to extract location, size and installation dates (Fig. 1).

The authors then manually verified that the tens of thousands of candidates identified by the machine-learning system were indeed photovoltaic installations, filtering out

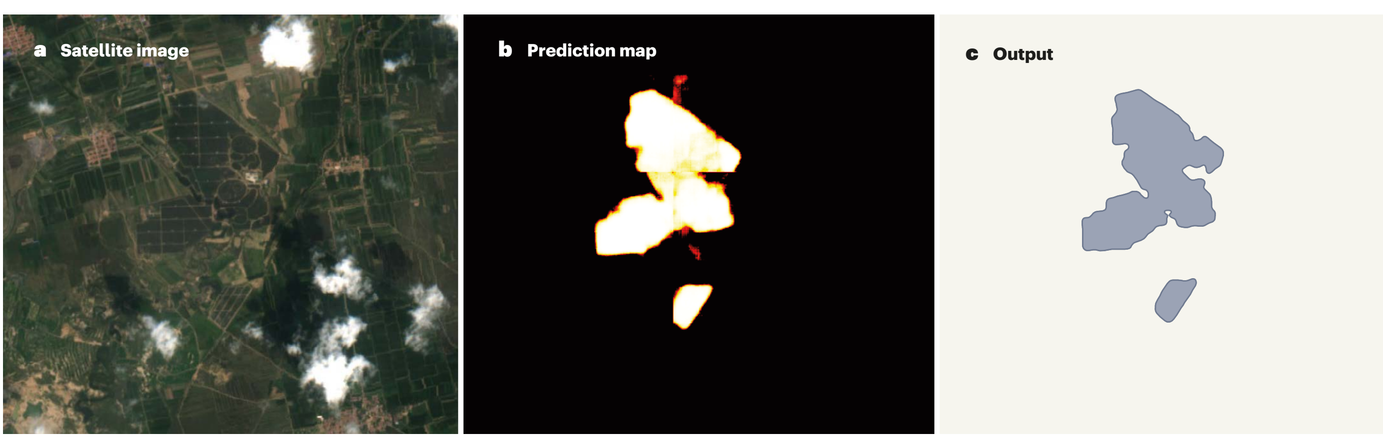

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Figure 1 | Mining satellite images to detect solar-panel installations. a, Kruitwagen *et al.*[1] have trained a machine-learning system to detect commercial-, industrial- and utility-scale solar-panel installations, by analysing satellite images such as this one. **b**, The machine-learning system generates a map that predicts the location and size of solar-panel installations (bright region). **c**, Further processing of the prediction map to eliminate false candidates produces a refined map as output.

chicken coops, greenhouses and so on. Such manual verification can impair reproducibility, and is therefore unusual in conventional applications of machine learning. However, it might be necessary when machine learning is being used to provide data for policymaking. The researchers have made available the data sets that they used to validate and test their method, as well as the resulting identifications. This will be tremendously valuable for further research in this area.

Kruitwagen and colleagues' results provide detailed information about many more solar installations than were previously described. On the basis of their detections, they also estimate the total global electricity-generation capacity of installed facilities, which is very close to the aggregate value provided by the International Energy Agency. Demonstrating the value of their granular facility-level data, they show that non-residential photovoltaic installations were most often developed on agricultural land, indicating a possible trade-off between renewable-energy development and food supply.

So what are the next directions for this field, now that Kruitwagen *et al.* have taken it to the global scale? One focus could be to increase the performance of this approach when identifying installations in different contexts. For example, landscapes — and the photovoltaic installations in them — can look very different from space in different geographical contexts, and so a model trained on data from one region might not make good predictions for another region. Ensuring that the machine-learning system does not systematically underperform for certain regions was a challenge for Kruitwagen and colleagues, and constitutes a problem to be addressed in the future. The same holds for other factors that determine what solar panels and their environments look like, such as types of building, technological characteristics, and the differences between urban and rural environments. This might become even more challenging when the goal is also to detect smaller-scale (residential) solar installations that were not covered in the authors' study.

Another task will be to measure the costs and benefits of the machine-learning approach. Initial concerns that machine learning would require too much effort and would result in low accuracy — and therefore would not add value to conventional approaches for collecting these data — have now been mitigated by initial successes. That said, high-resolution satellite images are expensive, and so is the large amount of computational power needed to train and deploy the model (for example, 71 megawatt hours of energy were used for Kruitwagen and co-workers' study). The costs and benefits to society of such approaches should therefore be evaluated regularly, and compared with the alternative option of collecting data directly.

In this regard, Kruitwagen and colleagues' study is a superb example of the value of machine-learning approaches — researchers, policymakers, international organizations and more across the world need access to trustworthy, regularly updated global data sets such as these. So who should bear the costs of this type of work and ensure that it is maintained and accessible to relevant stakeholders in the long run?

Research laboratories in universities have played a large part in developing similar machine-learning approaches focused on questions of societal relevance, for example to address climate change[10]. Universities and research institutions are ideally suited to conduct such work, but are unlikely to be the right kind of stakeholder to maintain and update large-scale databases over time. Instead, national and international agencies, not-for-profit organizations or publicly funded research entities could have the capacity, sustained funding and public-interest mandate to maintain the infrastructure needed to turn these data into a public good.

Ultimately, analysis of photovoltaic installations at large geographical scales is needed for real-world impact. Kruitwagen *et al.* show that machine learning offers an attractive option for gathering data at such scales when information is not collected through other means.

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Neuroscience

A brain signal that makes mice hungrier for reward

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Release of opioid peptide in the brain leads food-deprived mice to eat more sugar than do mice that are well fed. This opioid signalling mechanism fine-tunes the reward value of food according to the animal's state. **See p.646**

Eating even a simple snack is much more pleasurable when you are hungry than when you are already well fed. During fasting, complex brain mechanisms evaluate an animal's internal state, as well as the caloric and pleasurable (hedonic) values of the food, to ultimately drive eating. In the brain, several molecular signalling systems act together in this process, including the opioid system, which is composed of several opioid peptides and their receptors. The latter are the targets of opioid drugs such as morphine and heroin that have strong pain-reducing and notoriously addictive properties[1,2]. The brain's opioid system contributes to the hedonic value of natural rewards such as food, sex and social interactions[3], but the exact opioid peptide signal and receptor involved, and where they interact, have been challenging to determine. On page 646, Castro *et al.*[4] identify an opioid-system-tuned brain circuit that drives hungry mice to eat more of a sugar reward than do well-fed mice.

The study by Castro and colleagues showed that mice that were deprived of food for 24 hours ate, on average, about three times as many sugar pellets as did mice that had had free access to food. The team found that, in hungry mice, opioid peptides called enkephalins are produced in a part of the brain that is central to reward processing, the nucleus accumbens (NAC)[5], where they bind to and activate local μ-opioid receptors. These receptors are present at the terminals (endings of projections) of incoming neurons that originate from the dorsal raphe nucleus (DRN), which is known as the main centre for mood control. The enkephalin–receptor interaction in the NAC blocks the activity of these incoming neurons, interrupting a communication