Mapping solar array location, size, and capacity using deep learning and overhead imagery

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\textbf{Abstract}—The effective integration of distributed solar photovoltaic (PV) arrays into existing power grids will require access to high quality data: the location, power capacity, and energy generation of individual solar PV installations. Unfortunately, existing methods for obtaining this data are limited in their spatial resolution and completeness. We propose a general framework for accurately and cheaply mapping individual PV arrays, and their capacities, over large geographic areas. At the core of this approach is a deep learning algorithm called SolarMapper – which we make publicly available - that can automatically map PV arrays in high resolution overhead imagery. We estimate the performance of SolarMapper on a large dataset of overhead imagery across three US cities in California. We also describe a procedure for deploying SolarMapper to new geographic regions, so that it can be utilized by others. We demonstrate the effectiveness of the proposed deployment procedure by using it to map solar arrays across the entire US state of Connecticut (CT). Using these results, we demonstrate that we achieve highly accurate estimates of total installed PV capacity within each of CT’s 168 municipal regions.

\textbf{Index Terms}— solar energy, detection, object recognition, satellite imagery, photovoltaic, energy information.

I. INTRODUCTION

The quantity of solar photovoltaic (PV) arrays has grown rapidly in the United States in recent years [1,2], with a large proportion of this growth coming from small-scale, or distributed, PV arrays [3,4]. Distributed PV offers many benefits [5], but integrating it into existing power grids is challenging. A key ingredient for understanding PV growth factors, and effectively integrating new PV into existing grids, is high quality data. This includes, for example, the locations, sizes, and power generation capacities of existing arrays. Several organizations have begun collecting or publishing PV information, including the Interstate Renewable Energy Council (IREC) [6], Greentech Media [7], and the US Energy Information Administration (EIA) [8][9].

Although the available data on distributed PV is expanding, it is still difficult to obtain. Existing methods of obtaining this data, such as surveys and utility interconnection filings, are either unavailable publicly or time consuming to retrieve through PDF documents that have yet to be fully digitized and are sometimes incomplete. They are also typically limited in spatial resolution to the state or national level [3,6]. For example, the EIA began reporting state-level distributed PV data at the end of 2015 [8].

A. Practical large-scale collection of solar PV data

In this work we propose a general framework for accurately and relatively cheaply identifying individual PV arrays, their sizes, and power generation capacities over large geographic areas. At the core of this approach is a deep learning model that we have developed called SolarMapper, which can automatically map individual PV arrays in high resolution overhead imagery (e.g., satellite imagery, or aerial photography). We use the term mapping to denote the process of pixel-wise labeling of objects in geospatial data, such as overhead imagery. An illustration of SolarMapper operating overhead imagery in Connecticut, U.S.A. is illustrated in Fig. 1(a).

SolarMapper generates a pixel-wise labeling of the solar arrays in overhead imagery, from which additional information can be inferred. In our approach we first identify panels that are likely to be located on the same structure – termed \textit{installations}. We then infer information including the shape, surface area, and power generation capacity of each installation. This process is illustrated for a small patch of
overhead imagery in Fig 1(b). Finally, as shown in Fig 1(c) the information can be aggregated over any desired spatial region: cities, counties, or over census tracts.

**B. Contributions of this work**

In this work we present technical details of the SolarMapper tool, along with comprehensive results demonstrating the effectiveness of SolarMapper (and surrounding framework in Fig. 1) for large-scale mapping of small-scale solar arrays. Towards this end, we provide a robust estimate of the SolarMapper’s performance capabilities on a massive dataset of overhead imagery. We also publicly release the software for SolarMapper, and present a simple general guide for applying it to new geographic locations, or different imaging hardware. We demonstrate the effectiveness of this approach by employing it to map solar arrays, and their energy generating capacities, over the entire US state of Connecticut (CT) – over 14,000 km$^2$ – and present several metrics to demonstrate that the results are highly accurate.

**C. Organization of the paper**

The content in the body of this manuscript is focused on presenting the major results of our work, while several forthcoming appendices will provide further details about our methods. We begin with a brief review of recent related research in Section II. Section III presents the broad technical details of the SolarMapper tool, as well as our estimates of its performance. Section IV presents a guide for applying SolarMapper to new geographic locations, and a case study of applying it to the entire US state of Connecticut (CT). In Section V we describe how capacity can be estimated from SolarMapper’s output, and use this approach to obtain accurate estimate the installed solar capacity in each of CT’s 168 municipalities. Finally, Section VI presents our conclusions.

**II. RELATED WORK**

The idea of using computer algorithms to automatically detect solar arrays in VHR imagery was first investigated in [10] (on a small-scale dataset) and [11] (on a larger scale dataset). These initial PV detection algorithms were designed using traditional image recognition approaches, consisting of hand-crafted image features and supervised classifiers [10,11]. These algorithms demonstrated the concept of mapping solar arrays in overhead imagery, but did not achieve performance that was likely to be useful in most applications.

Recently, convolutional neural networks (CNNs) have yielded groundbreaking recognition performance on many image recognition tasks [12], and CNNs were subsequently applied for solar array mapping [13–15]. CNNs were originally designed to provide a single prediction for an entire input image, e.g., indicating whether an image contains or does not contain a solar array. Of note was the work in [13,14] that employed semantic segmentation CNNs, which are designed to provide pixel-wise labels of an input image. In this work, and in the context of remote sensing, we have referred to the semantic segmentation task as mapping. Substantially better performance was achieved for both solar array object identification, as well as estimating their shape/size, when using semantic segmentation models [14].

These works with semantic segmentation (or Mapping) CNNs demonstrated that solar mapping could achieve practically-useful levels of performance. Additional work around the same time demonstrated the possibility of inferring energy generation capacity using only overhead imagery [16]. This prior work collectively demonstrated the potential to create a system for reliably collecting small-scale solar PV information over large-scale areas.

This work bridges some of the gaps of prior work. First, this work brings together the individual prior techniques, and describes how they can be used in a single practical system. Prior work was limited by the size and diversity of the datasets used to train and test the CNN algorithms. We employ a dataset of hand-labeled solar arrays of unprecedented size and diversity. Finally, in contrast to prior work, we demonstrate that these techniques can be deployed in new and large geographic areas to achieve practically useful results.

**III. SOLARMAPPER: A TOOL FOR MAPPING SOLAR ARRAYS IN OVERHEAD IMAGERY**

**A. Overview of SolarMapper**

SolarMapper is essentially a state-of-the-art deep convolutional neural network (CNN) that has been trained to recognize solar arrays in overhead imagery. SolarMapper receives an overhead image as input, and returns a probability “map”, indicating the likelihood that a solar array exists at each pixel location in the original imagery. In order to obtain a categorical label at each pixel – panel or not a panel - we can apply a threshold to each pixel value (e.g., 0.5), above which a pixel is assigned a label of one (panel), and otherwise zero (non-panel).

Training a CNN requires a set of imagery, termed a training dataset, for which the true labels of each pixel are known. CNNs are comprised of (often) millions of parameters that each influence its output; training a CNN involves iteratively adjusting these parameters until it produces accurate labels for the training dataset. To achieve the best performance, CNNs require training datasets that are large and diverse. SolarMapper was trained on the Duke California Solar Array dataset [17], comprising over 400km$^2$ of imagery across three cities in the US state of California, and encompassing 16,000 hand-labeled solar arrays. To date, this dataset is the largest and most diverse dataset of fully-annotated solar arrays.

**B. The performance of SolarMapper**

To assess the performance of SolarMapper, we employed a two-fold cross-validation procedure on the Duke California Solar Array Dataset[17]. Cross-validation is a conventional procedure within the machine learning community to estimate the performance of supervised (i.e., trained) models, such as CNNs. Using this procedure we assessed two different qualities of SolarMapper’s performance: (i) pixel-wise labeling accuracy and (ii) object-wise detection accuracy.

To assess pixel-wise performance we use the intersection-over-union (IOU) metric, which is popular for scoring pixel-wise labeling tasks (often called semantic segmentation) in
the computer vision research community [18,19]. Given two sets of pixels denoted by A (e.g., predicted panel pixels) and B (e.g., true panel pixels), IOU is given by \[ \text{IOU} = \frac{|A \cap B|}{|A \cup B|} \] Here the vertical bars indicate the cardinality of the set. An IOU of one is achieved if the predicted array pixels perfectly overlap with the true array pixels. If there is no overlap, the IOU will be zero. The IOU values for SolarMapper are presented in Table I, broken down by each of the three cities in the dataset.

Table 1: Intersection-over-union (IOU) performance estimates for the Duke California Solar Array dataset

|           | Fresno | Modesto | Stockton | Aggregate |
|-----------|--------|---------|----------|-----------|
| Precision | 0.67   | 0.66    | 0.69     | 0.67      |

To assess object-wise performance, we identify solar array installations in both the true array mappings and the SolarMapper output, as shown in Fig. 1(b). We say that a predicted panel installation is a correct detection if it achieves an \( \text{IOU} \geq 0.5 \) with a true panel installation. Otherwise it is considered a false detection. This is a common criterion for detection within the computer vision community [20,21]. Any arrays that were not linked to a predicted installation are considered missed detections. Based on this procedure, we can obtain the precision (proportion of detections that were correct) and recall (proportion of true installations that were detected). Precision and recall are common measures for image-based object detectors [20,21], including in remote sensing applications [11,22]. These results are summarized below in Table 2.

Table 2: Object-based performance of SolarMapper in CA.

| City       | Precision | Recall | F1 Score |
|------------|-----------|--------|----------|
| Fresno     | 0.77      | 0.78   | 0.77     |
| Modesto    | 0.73      | 0.75   | 0.74     |
| Stockton   | 0.73      | 0.7    | 0.71     |
| Overall    | 0.76      | 0.77   | 0.76     |

IV. DEPLOYING SOLARMAPPER TO A NEW LOCATION: A CASE STUDY IN CONNECTICUT

As discussed in the introduction, a major contribution of our work is to provide SolarMapper as a tool for use by the broader research community. In this section we discuss first how we deployed SolarMapper to map solar arrays in a new location using fine-tuning, a form of transfer learning. Second, we present a method of validating fine-tuning results in a new location and demonstrate that the fine-tuning approach achieves highly accurate results.

A. Fine-tuning SolarMapper for Connecticut

Unfortunately, applying SolarMapper to a new location is not a trivial endeavor. This is because of the high likelihood that differences may exist in the characteristics of the imagery at a new location compared with the imagery on which SolarMapper was trained. Such qualitative differences can cause SolarMapper to perform (i) unpredictably and (ii) poorly, making it unusable for most practical applications.

Such changes in the imagery may arise due to changes in the underlying landscapes (e.g., vegetation versus desert), changes in the appearance of urban structures on which solar arrays reside (e.g., roof colors, textures), changes in lighting conditions (e.g., due to changes in hour of day), changes in the camera perspective, and more. This is a problem shared by all supervised machine learning algorithms and a major ongoing challenge recognized for remote sensing applications in particular [23,24].

Fortunately, there is a practical solution to this problem, referred to as transfer learning. In our context, transfer learning aims to leverage the similarity between finding solar arrays in the Duke California Solar Array dataset [17] (the training data for SolarMapper), and finding arrays in new locations or imagery (e.g., in CT). We use a now widely-used form of transfer learning, called fine-tuning, where the idea is that SolarMapper’s parameters, once trained in CA, should require relatively little adjustment to perform well in CT. Therefore we should be able to use relatively little local hand-labeled data to adapt, or fine-tune, the parameters to achieve highly accurate results. In fact, in most cases, fine-tuning necessitates a small fraction of the training data required to train a full CNN. The process of fine-tuning for CT is illustrated in Fig. 2 below. For our fine-tuning experiments here we hand-annotated just 15 \( km^2 \) of imagery in CT, corresponding to 0.1% of its total area.

![Fig. 2. An example of an aerial image (top) and its corresponding confidence map (bottom). In both images the true solar PV locations have been annotated in red. The confidence map is the output of stage two in the detection algorithm.](image-url)

B. Assessing the performance of fine-tuning

In contrast to our dataset in CA, in CT we do not have large numbers of labels, making it difficult to evaluate performance. This will generally be the case when deploying SolarMapper to a new geographic region, because obtaining large quantities of annotated imagery is time-consuming. However, to demonstrate the effectiveness of SolarMapper in such deployment settings, we manually inspected the imagery over two full municipal areas in CT. During inspection the predicted solar arrays were overlaid on the overhead imagery, allowing human inspectors to judge SolarMapper’s predictions. If a predicted array overlapped with a solar array, it was considered a detection, and otherwise it was a false detection. Any true arrays that were found without an
overlapping predicted panel were considered missed detections. This inspection procedure is much faster than hand annotation, and thereby provides a viable means to quickly assess object-based performance on new imagery.

The results of this inspection are presented in Table 4, indicating excellent performance, although we note that this scoring criteria is somewhat more optimistic than our previous object-based measures in Section III.B because we do not set a minimum IOU threshold between true panels and detections in order to establish a correct detection.

Table 3: Object-based performance of SolarMapper in CT, based on a visual inspection of two municipalities: Durham and Trumbull.

| Municipality inspected | Precision | Recall | F1 Score |
|-----------------------|-----------|--------|----------|
| Durham                | 0.91      | 0.75   | 0.82     |
| Trumbull              | 0.86      | 0.88   | 0.87     |
| Overall               | 0.88      | 0.83   | 0.85     |

V. ESTIMATING ENERGY GENERATION CAPACITY IN CONNECTICUT

In this section, we demonstrate how SolarMapper can be employed to map power generation capacity over large areas, using only the original overhead imagery, and the mappings provided by SolarMapper (derived from overhead imagery). We demonstrate the proposed approach in the state of CT, building on the results in Section IV. We are uniquely able to validate our capacity predictions in CT because of estimates of the installed solar capacity in each of its 168 cities (termed municipalities) are provided via the Solar Scorecard Project\(^1\). We begin by providing a brief overview of our general approach for capacity estimation, and then presenting the results.

A. Estimating capacity from overhead imagery

Our approach for inferring capacity relies on the relationship that the power generation capacity of a solar array, denoted \(c\), is proportional to its surface area, denoted \(a\). If we assume some uncertainty in the relationship, then we obtain the following simple linear regression model to predict the capacity of the \(i^{th}\) array:

\[
c_i = \gamma a_i + \eta_i.
\]

Here \(\gamma\) serves as a proportionality constant, indicating the capacity per unit of surface area. The value of \(\gamma\) will likely vary for each solar array depending upon factors such as its manufacturer, its level of upkeal, and its cell type (e.g., thin film, polycrystalline, etc.); but it is approximated here as a constant across arrays. The term \(\eta_i\) refers to the error of the predictions for the \(i^{th}\) array.

Using array mappings from SolarMapper, we can acquire the (approximate) surface area of each array by summing the number of its pixels, which have a known spatial extent. This basic model and approach were demonstrated (with a different mapping algorithm) to yield accurate estimates of capacity for individual arrays in [16].

To employ this model in practice however, one must obtain an estimate for \(\gamma\), and we propose two approaches. The first is to use prior information, perhaps from solar PV manufacturers, to estimate a likely value for \(\gamma\). Alternatively, and the method used in [16], is to use a small set of known values of capacity, and their areas estimated using SolarMapper, to infer \(\gamma\). This can conceivably be accomplished using linear regression (as in [16]) with a very small number of \((c_i, a_i)\) samples.

In this work we employ a modified version of the latter approach, in which we use just one municipal-level capacity value to infer \(\gamma\). Furthermore, we find that using simple color features extracted from the overhead imagery, it is possible to infer a unique \(\gamma\) for each solar array.

\(^1\) http://www.ctsolarscoreboard.com/

Fig. 3. (a) Installed small-scale solar PV capacity in CT, and (b) the capacity estimated by SolarMapper. Upon investigation, Groton was found to have accurate array predictions, and was identified as an outlier and removed from our experiments (see Appendix IV).

B. Validating the capacity estimates

Using the approaches outlined in Section V.A, we estimated the power capacity of each detected solar array in CT, and then summed the capacity of all arrays within each municipal region. To evaluate the accuracy of our capacity estimates, we computed the Pearson correlation coefficient between our capacity estimates and those reported in the CT Solar Scorecard dataset. If we use a model that assumes a fixed value of \(\gamma\) for all arrays, we achieve a correlation coefficient of 0.88. Using color imagery to estimate a unique value of \(\gamma\) for each solar array results in a slightly higher correlation coefficient of 0.91. In both cases the p-values were less than 0.01. Fig. 5
presents a visualization of the estimates provided by SolarMapper, and the officially reported values. The results are visually consistent with the high correlation coefficients. We note in Fig. 5 that one municipal region, Groton, was removed from our analysis because it is an outlier with a known cause.

These results also provide an additional validation of the mappings produced by SolarMapper. The values of \( \alpha \) used in equation (3) to estimate capacity are based directly on the number of pixels detected by SolarMapper. Therefore, it is unlikely that capacity estimation would be accurate unless SolarMapper provided accurate values of \( \alpha \) for each panel. This does not provide a precise measure of SolarMapper’s performance, but a practical benchmark, since it does suggest that SolarMapper was sufficiently accurate to support municipal capacity estimation.

VI. CONCLUSIONS

In this work we presented SolarMapper, a framework for mapping small-scale solar arrays over large geographic areas. At the core of SolarMapper is a deep convolutional neural network (CNN) that we trained to identify solar arrays in overhead imagery, after which we show how to infer area and capacity for individual array installations. Information for individual arrays can then be aggregated over any desired spatial regions (e.g., cities, counties, states, etc.).

In this work we conducted two main experiments. The first experiment demonstrated that SolarMapper can provide highly accurate locations, shapes, and sizes of individual solar arrays over large areas. This provides strong evidence of this methodology as a scalable means to obtain high quality solar array information over large areas.

The second experiment demonstrated how SolarMapper could be used as a tool by researchers, policymakers, and utilities for their own work. We presented a simple procedure for applying SolarMapper to new geographic locations, and then demonstrated it to map solar arrays, and their capacities, over the entire US state of Connecticut. We also demonstrated that the results were highly accurate, making SolarMapper a viable tool for broader use.

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