Remote Sensing Assessment and Monitoring of Distributed large and small scale Solar Panel Arrays

A report on baseline Computer Vision models and algorithms for optimizing generation of a Planetary dataset

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CCOM 6050: Final Project – Final Report

Contents

1 Introduction

1.1 General Objective

Regional-scale surveys of distributed *rooftop PV solar panels*, and **site-level, short-term forecasting** of *solar irradiance* used to estimate local PV power generation.

This assessment will primarily produce counts of installed systems, estimates of surface area, estimated PV generation potential while monitoring will provide forecasts of local solar irradiance which are used to model estimates of PV energy generation at specific sites.

The work developed for this thesis proposal is particularly inspired by and seeks to build upon the work realized, methodologies outlined, research gaps identified, and future work outlined in[?],[?],[?],[?],[?],[?],[?],[?],[?], and[?].

1.2 Problem Statement and Motivation

The global response to climate change requires our civilization to implement a rapid transition to renewable energy sources in an effort to decarbonize the energy sector as much as possible. The fastest growing renewable energy source is by far *photovoltaic* (PV) solar energy [cite]. Growing at over 41% per year on average since 2009[?], PV solar energy has far outpaced other renewable energy sources such as concentrated solar power (CSP), hydroelectric storage, geothermal energy, and, to a lesser extent, wind energy. This rapid growth has led to significant progress in international development goals such as the United Nations Sustainable Development Goals (SDG) which, among other things, addresses the population level needs for clean and affordable energy, and actions to tackle climate change and its impacts[?].

Historically, one of the most effective means to ensure global cooperation and uniform implementation of environmental and energy policies has been through the establishment of multilateral international agreements such as the Montreal Protocol, the Kyoto Protocol, and, most recently, the Paris Climate Accords signed by (add figure of % of countries signed and ref) countries. This agreement resulted in *non-binding* commitments to reduce greenhouse gas emissions and goals to limit global warming to 1.5 - 2.0 degrees Celsius above pre-industrial levels. Notably, 87% of these Nationally Determined Contributions (NDCs) aim to increase the share of renewable energy in their energy mix with half specifying empirical generation figures[?]. **To maintain any semblance of international accountability to these commitments, these NDCs require extensive and accurate global monitoring and validation of any expansion of renewable energy infrastructure.**

To address this *international policy problem* there has been a variety of efforts to assess the progress of each renewable energy source leading to recurring reports, inventories, assessments, and databases at the global, regional, and national levels. Many of these efforts prove insufficient due to only providing aggregated summaries or statistical extrapolations at the national level (IRENA, IEA, BP), or being limited to specific regions (i.e. primarily Europe, North America, and China). Particularly in the case of PV solar energy, there has been very significant progress over the last decade in the development of remote sensing and deep learning methods to assess the distribution of PV solar energy at the site, regional, and global levels (cite the many PV assessment papers). Most recently, a collaboration between Microsoft, the Nature Conservancy, and Planet Labs[?] has produced *"Global Renewables Watch"*, a public dataset of industrial, commercial, and utility-scale PV solar energy and wind energy installations firmly establishing the **feasibility of using high-resolution satellite imagery and deep learning methods to assess the distribution of renewable energy infrastructure at the Planetary scale**.

These publications and datasets have primarily focused on large-scale, utility-scale PV solar energy installations (i.e. badly labeled "solar farms") which are typically located in remote areas with broad land availability and low land use conflicts. However, for some countries, land comes at a premium and concentrated large-scale solar energy installations are either not economically or politically feasible due to not being the most efficient use of land and other land use conflicts. This leads to countries where distributed, small-scale rooftop or building-integrated PV solar energy installations make up a significant portion of the total installed capacity which is not captured in assessment limited to large-scale installations. For example, Robinson et al[?] and Kruitwagen et al[?] use a $\geq$ 10KW threshold for the solar arrays they are analyzing which excludes most residential installations.

Additionally, intermittent renewable energy sources bring about a second *technical problem* that also calls for assessments and inventories at a smaller spatial **and** temporal scale. The intermittency of renewable energy sources such as wind and solar energy means that energy grid operators require accurate short-term forecasts of energy generation to ensure that national electric grid supply and demand are balanced. PV solar energy is particularly sensitive to local weather conditions and received solar irradiance which can both be monitored using remote sensing methods and local weather stations. There has been recent work in the use of geostationary satellites with high temporal resolution to provide short-term forecasts of solar irradiance at the site level[?], the use of spectral reflectance features in Computer Vision (CV) models for PV solar array detection[?], and advances in spatio-temporal data fusion methods to improve the temporal resolution of very-high-resolution (VHR) satellite imagery[?].

This project looks to outline the work required to address these interconnected challenges by tackling three core subproblems leveraging remote sensing data and advances in deep learning methods:

1.2.1 [CCOM6120] Subproblem 1:

Detection and Segmentation of distributed rooftop PV Systems using Computer Vision baseline models The first fundamental challenge lies in the automated, accurate, and scalable identification and geometric characterization of distributed rooftop PV panels using very-high-resolution (VHR) multispectral satellite imagery. Generating reliable, up-to-date inventories of these small, dispersed assets is crucial for granular PV potential assessments[?][?], infrastructure planning, monitoring deployment rates against policy goals[?], and producing the georeferenced geometry data required for accurate site-level solar irradiance forecasting and PV energy generation estimates[?]. We will use the final project for CCOM6120 as preliminary work on this subproblem. We will explore baseline segmentation model architectures (e.g. UNet, FPN, PAN, SegFormer, etc.) and encoder combinations (e.g. ResNet, EfficientNet, ViT, Swin, etc.) and how they perform on some existing published datasets. As part of the project we will develop and establish some baseline data processing pipelines, model training workflows, and evaluation metrics.

1.2.2 [CCOM6050] Subproblem 2:

Hierarchical Spatial Clustering of global PV installations to optimize dataset generation Given a large, globally distributed set of Points-of-Interest (PoIs) representing Photovoltaic (PV) solar panel installations (potentially hundreds of thousands to millions), the objective is to efficiently identify and retrieve subsets of relevant satellite imagery (rasters) from open access archives (e.g., STAC catalogs) that maximize the spatial and temporal coverage of the PoIs. Our *Optimization Goal* is to design an algorithmic framework that **maximizes** the spatial and temporal coverage of the PoIs by the fetched rasters while simultaneously **minimizing** the number of raster queries and the volume of data downloaded and processed for model training.

Why it's a problem:

- Naive querying strategies (i.e. per POI, or per cluster of POIs) quickly becomes very inefficient for large, globally distributed datasets of PoIs: leads to excessive API calls or HTTP requests, redundant data retrieval, and high processing overhead.
- PV installations are naturally spatially clustered: *but* these clusters are not known a priori and can span across arbitrary administrative boundaries or diverse geographic contexts.
- The spatial and temporal coverage of the PoIs is not uniform: being able to *dynamically adjust* the size and shape of the query bounding boxes based on the density of PoIs in a given area and the extent of specific raster items is crucial for efficient data retrieval.

We will use the final project for CCOM6050 as preliminary work on this subproblem. We will explore the use of data fusion with geospatial context from Overture Maps, the effectiveness of aggregating our hundreds of thousands of PoIs using Discrete Global Grid Systems (DGGS) such as Uber's H3, and how we can leverage hierarchical spatial clustering algorithms over our H3 hexagon cells to produce a data structure that can be used to efficiently query and retrieve satellite imagery from open access catalogs.

1.2.3 [Future Thesis Work] Subproblem 3:

Solar irradiance forecasting at specific sites

The second major challenge is analyzing ~~high-temporal-resolution surface reflectance~~ (intra-hour) time series of geostationary satellite imagery to produce accurate short-term forecasts of solar irradiance at specific sites. This is a critical requirement for energy grid operators to ensure that supply and demand are balanced, especially in the case of intermittent renewable energy sources such as wind and solar energy.

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2 Background

2.0.1 Earth Observation and Remote Sensing

Remote sensing (RS) refers to the process of acquiring images and data of the planet's surface using a variety of remote sensors in satellite and aerial vehicles (add citations from my prev paper). These sensors analyze electromagnetic radiation reflected or emitted from objects on the Earth's surface, which is then processed to extract information about the objects and their properties. Besides traditional electro-optical (ie panchromatic and 3-channel RGB images (cite)) modern RS employs a variety of sensors and modalities such as multispectral (four or more non-overlapping bands in the electromagnetic spectrum), hyperspectral (more than 100 narrow bands), and even active sensors such as microwave altimeters or Synthetic Aperture Radar (SAR) that emit their own radiation and measure the reflected signal to "see" at night and through atmospheric obstructions like clouds and fog (cite myself or refs from prev paper). Analysis of source data from these remote sensors must handle a variety of nuanced characteristics of each sensor and the produced data. For our purposes and the scope of this report, we will limit our discussion to the following characteristics:

- Spatial resolution: The level of detail in an image, typically measured in meters per pixel.
- Spectral resolution: The ability of a sensor to distinguish between different wavelengths of light.
- Temporal resolution: The frequency at which a sensor captures data over the same location.
- Radiometric resolution: The sensitivity of a sensor to detect variations in intensity, often represented by bit depth.
- Earth Observation (EO) data types:
    1. Raster data: Gridded data representing continuous surfaces.
    2. Vector data: Discrete data represented as points, lines, or polygons.
    3. Time series data: Sequential data capturing changes over time over a specific area.
    4. Geospatial data cubes: Multidimensional arrays combining spatial, temporal, and spectral dimensions.

2.0.2 Computer Vision

Computer Vision (CV) is a subfield of Artificial Intelligence and a discipline that deals with the problem of interpreting and extracting meaningful information from images (cite myself or refs from prev paper) in a manner similar to human vision. This field has seen significant advancements in recent years, particularly with the rise of deep learning methods and the spread of large, labeled datasets for many applications. RS and EO has seen an explosion of interest, publications, and datasets for DL methods since 2015 (cite EO paper from cloud computing course). Relevant CV tasks for our purposes include:

1. Scene Classification: Assigning a label to an entire image based on its content (e.g., classifying an image as containing a PV array, rooftop, or vegetation).
2. Object Detection: Identifying and localizing specific object classes (e.g., PV panels) within an image with (georeferenced) bounding boxes.
3. Semantic Segmentation: Classifying each pixel in an image into predefined categories (e.g., PV panel array, rooftop, vegetation, background).
4. Instance Segmentation: Similar to semantic segmentation, but differentiates

between *individual* instances (e.g., distinguishing between different PV panel arrays).

Some relevant CV architectures include Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), Generative Adversarial Networks (GANs), and CNN-Transformer hybrids.

2.1 SpatioTemporal Asset Catalogs

2.2 Discrete Global Grid Systems

2.3 Minimum Spanning Trees for Spatial and Hierarchical Clustering

2.4 Research Gaps and Contribution Goals

1. Measure performance impact of SOTA Computer Vision architectures (e.g. ViT, Swin, CNN-Transformer hybrids) currently lacking in most recent publications and compare to established baselines (e.g. UNet, FPN, PAN, etc.)
2. Regional, and global surveys are limited to large-scale farms using medium resolution sensors ($\sim 10m$/pixel). On the other hand, studies using VHR aerial imagery usually only have coverage for local, city-scale surveys. We will use *global 30cm yearly basemaps* or open access catalogs from VHR MSI sensors, primarily from Maxar, to perform a global survey of PV installations that includes both large-scale farms and distributed rooftop PV systems.
3. Almost all notable studies (with the exception of (cite GloSoFarID)) exclusively use RGB image bands. Measure impact of use of PV-specific spectral indices[?] and specifically the benefits of including NIR + SWIR bands available in Maxar sensors
4. Develop a solution that consciously tackles the challenges identified in[?] for evaluating and performing comparisons of different remote sensing solar array assessment methodologies (distribution drift, test data quality, level of spatial-aggregation, and proprietary data)

3 Methodology

3.1 Datasets and Processing

3.1.1 RS imagery and locations of PV arrays

- Dataset 1 - Description, source
- Dataset 2 - Description, source

3.1.2 RS Datasets for STF

- Dataset 1 - Description, source
- Dataset 2 - Description, source

3.1.3 Pre-processing steps

3.2 Implementation Details

3.2.1 Python Libraries and other computational tools

- *Python 3.10* - programming language
- *PyTorch 2.0* - deep learning framework
- *jupyterlab* - web-based interactive development environment for Jupyter notebooks
- *numpy + xarray* - array processing
- *Geopandas* - Geospatial data manipulation and analysis
- *duckdb* - an in-process SQL OLAP database management system
- *cubo* - a library for working with cuboids (3D arrays) in Python
- *openeo* - python client for the OpenEO API
- *Rasterio* - Raster data reading and writing
- *GDAL* - Geospatial data abstraction library
- *mamba* - a faster alternative to the conda package manager
- *rastervision* - a framework for computer vision and deep learning in remote sensing
- *PyTorch Lightning* - a lightweight wrapper for PyTorch to help with training and testing
- *TorchGeo* - a library for deep learning on geospatial data which includes datasets and pretrained models
- *torchmetrics* - a library for computing model evaluation metrics in PyTorch

3.2.2 Hardware and Compute Resources

- Personal Developer Machine: 16”Macbook Pro 2021, M1 Max, 32GB RAM, PyTorch supported mps accelerator
- Google Colab Pro+: $50/month subscription used to train efficiently train models on cloud GPUs (up to Nvidia A100) and test clustering algorithms on GPU
- Google Earth Engine [Future]: cloud-based geospatial analysis platform for large-scale remote sensing data processing
- Microsoft Planetary Computer [Future]: cloud-based geospatial analysis platform for large-scale remote sensing data processing
- AWS [Future]: hosts many open-access geospatial datasets including STAC Catalogs

3.2.3 Code Repository

As of writing, the Github repo where this report and associated code is hosted is public.

3.3 Evaluation

3.3.1 Computer Vision Models

- Dice Loss
- mean Intersection over Union (mIoU):

3.4 Expected Results

1. Subproblem 1:
    - Description of the expected results
    - Description of the expected results
2. Subproblem 2:
    - Description of the expected results
    - Description of the expected results
3. Subproblem 3:
    - Description of the expected results
    - Description of the expected results

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4 [CCOM6050] Adapting Spatial Hierarchical Clustering Algorithms to our application

Here we will go into detail on our algorithm design and approach for optimization of STAC queries when generating our dataset.

4.1 Data Ingestion and Preprocessing

4.2 H3 Indexing and Spatial Aggregation

4.3 Graph Construction from H3 Grid Cells

4.4 Minimum Spanning Tree (MST) Construction

4.5 Generating a Hierarchy of Clusters: Dendogram Construction and H3 multi-resolution

4.6 Optimized STAC Querying

5 Literature Review

5.1 [CCOM6050] Data Fusion Reviews

5.1.1 2019-RS-DF-Multisource

- Title: "Multisource and Multitemporal Data Fusion in Remote Sensing: A Comprehensive Review of the State of the Art"
- Authors: Pedram Ghamisi; Behnood Rasti; Naoto Yokoya; Qunming Wang; Bernhard Hofle; Lorenzo Bruzzone
- Year: 2019
- Link/Source: 10.1109/MGRS.2018.2890023
- Main objective:
- Methodology used:
- What I got out of the paper:
  - "bird's eye view" of contributions in:
    - pansharpening and resolution enhancement
    - multitemporal data fusion
  - Traditionally in Remote Sensing (RS), there are four dimensions that provide information:
    - Spatial: 2D (x,y) coordinates
    - Temporal : 1D (t) time
    - Spectral: 1D (λ) wavelength
    - Radiometric: 1D (r) numerical precision in a pixel's radiance/reflectance/intensity values
  - RS measurement process is explored via describing the four components of a "physical model":
    - Scene model: defines the subject of interest
    - Atmosphere model: defines the transform of Electromagnetic Spectrum (EMS) from surface to sensor
    - Sensor model: defines the measurement process (e.g. signal-to-noise ratio (SNR), sweep time, nadir angle, number of bands, etc.)
    - Image model: defines the sampling process (e.g. pixel size, spatial resolution, etc.)
  - **"All data fusion methods attempt to overcome the above measurement and sampling processes"**
    "Understanding these [differences in] measurement and sampling processes is... key

to characterizing methods of data fusion” $\implies$ can be approached as a reconstruction problem…

- Spatio-Spectral data fusion
  * Pansharpening: a specific case of spatio-spectral fusion where a high-resolution panchromatic image is fused with a lower-resolution multispectral image.
    This fusion process attempts to preserve the spectral information of the multispectral image while enhancing the spatial resolution for *all* bands.
  * Most methods can be categorized into:
    1. Component substitution: spectrally transforms MS data into a new feature space to separate spatial and spectral information,
       then substitutes the spatial component is substituted for the high-resolution panchromatic image while using histogram matching to adjust the PAN intensity to match the original spectral information.
       · Pros: *high spatial fidelity*; *low computational cost*; *robust against misregistration errors (i.e. spatial misalignment)*
       · Cons: *suffer from global spectral distortion*; *lower spectral fidelity*
       · Methods include:
       (a) **Intensity-Hue-Saturation (IHS)**
       (b) Principal Component Analysis (PCA)
       (c) Gram-Schmidt (GS)
    2. Multiresolution analysis: extracts spatial high-frequency components from the panchromatic image and injects with coefficients into the low-resolution multispectral image.
       · Pros: Spectral consistency (e.g. no spectral loss)
       · Cons: *Higher computational complexity and cost*
       · Methods include:
       (a) Box filtering
       (b) Gaussian filtering
       (c) Bilateral filtering
       (d) Wavelet transform
       (e) Curvelet transform
    3. Geostatistical analysis: can preserve the spectral properties of the original coarse image while enhancing the spatial resolution.
       · Pros:
       · Cons:

    · Methods include: several types of *kriging* (spatial interpolation) which are used to estimate unmeasured values based on neighboring values

  4. Subspace representation: uses a subspace spanned by a set of basis vectors to analyze intrinsic spectral characteristics
    · Pros:
    · Cons: *High computational cost*; *can introduce spectral artifacts*
    · Methods include: Bayesian analysis, Matrix Factorization, Spectral Unmixing
  5. Sparse representation: captures the spectral signatures of materials in an image patch using a sparse representation with a few basis vectors
    · Pros: *Efficient storage and processing*; *high spectral fidelity*; *sparse representation can be used in downstream CV tasks*
    · Cons: *Targeted for HSI-MSI fusion*; *very high computational cost*
    · Methods include: Hierarchical Pyramid models; extraction of spectral signatures;

* Some quantitative evaluation metrics:
  1. Peak Signar-to-Noise Ratio (PSNR): evaluates the quality of a reconstructed image by comparing the maximum possible power of a signal to the power of corrupting noise
  2. Spectral Angle Mapper (SAM): determines the similarity between a transformed image spectrum and a reference spectrum by calculating the angle between their vector representations in the spectral space
  3. ERGAS (*erreur relative globale adimensionnelle de synthèse*): measures image quality in terms of the per-band normalized mean error between the fused image and the reference image
  4. Q^{2n}: a global reconstruction quality index

– Spatio-temporal data fusion
  * "a technique to blend fine spatial resolution, but coarse temporal resolution data with fine temporal resolution, but coarse spatial resolution data"
  * **Most methods are based on the strong assumption of no abrupt changes in Land Cover and Land Use (LCLU) across time** (ok for our work if we focus on rooftops)
  * Methods mentioned:
    1. STARFM (Spatial and Temporal Adaptive Reflectance Fusion Model)
    2. ESTARFM (Enhanced STARFM)
  * Common sensor pairings:
    1. MODIS (daily; 0.25km-1km) + Landsat (16 days; 30m)

2. MODIS + Sentinel-2 (5 days; 10m)
3. GOES-R (5-60 min; 0.25-2km) + ??

- Key findings or contributions for our topic:
  - Outlines the centrality of Coherence for Data Fusion with RS data:

    "Data fusion is made possible because each dataset to be fused represents a different view of the same real world defined in space and time (generalized by the scene model), with each view having its own measurable properties, measurement processes, and sampling processes."

    $\Longrightarrow$ "one should expect some level of **coherence** between the real world (the source) and the multiple datasets (the observations)"
  - **Spatio-temporal fusion** was identified as the relevant type of fusion for our work:

    "A large focus of attention currently is on the specific problem that arises from the trade-off in remote sensing between spatial resolution and temporal frequency; in particular the fusion of coarse-spatial/fine-temporal-resolution with fine-spatial/coarse-temporal-resolution space-time datasets"
  - For an individual remote sensing platform, "there always exists a trade-off between spatial resolution and temporal resolution (revisit time)". This can be worked around with a constellation of multiple sensors.
  - A remaining major issue is how to conduct fair comparisons of performance and accuracy of different methods.

5.1.2 2024-DL-Data-Fusion

- Title: "A Comprehensive Review on Deep Learning-Based Data Fusion"'
- Authors: Mazhar Hussain; Mattias O' Nils; Jan Lundgren; Seyed Jalaleddin Mousavirad
- Year: 2024
- Link/Source: 10.1109/ACCESS.2024.3508271
- Main objective:
- Methodology used:
- Key findings or contributions for our topic:

5.2 [CCOM6050] Data Fusion Datasets

- Title:
- Authors:
- Year:
- Link/Source:

- Main objective of the paper:
- Methodology used:
- Number of annotations:
- Date range for annotations:
- Annotation locations:
- Key findings or contributions:

5.3 PV imagery and locations Datasets

5.3.1 2023-SDG-Maxar-PV-dataset

- Title: "A solar panel dataset of very high resolution satellite imagery to support the Sustainable Development Goals"
- Authors: Cecilia Clark [ex-Maxar]; Fabio Pacifici[Maxar]
- Year: 2023
- Link/Source: 10.1038/s41597-023-02539-8 — imagery — annotations
- Main objective of the paper: To provide a VHR satellite imagery dataset of annotated, primarily residential, solar panels to support UN's Sustainable Development Goals, and further improve solar panel detection models.
- Methodology used:
  Obtained 31 cm resolution satellite imagery and applied proprietary HD processing to generate 15.5 cm resolution imagery used for panel detection. Labels created with Object Detection model (YOLT) and validated by human annotators.
- Number of annotations: 2,542
- Date range for annotations: 2020/09/18
- Annotation locations: Southern Germany
- Key findings or contributions:
  The dataset is designed to support small object detection and focuses on annotated, primarily residential, solar panels. Includes paired native resolution (31 cm) and HD (15.5 cm) satellite imagery.

5.3.2 2021-global-PV-inventory

- Title: "A global inventory of photovoltaic solar energy generating units"
- Authors: L. Kruitwagen; K. T. Story; J. Friedrich; L. Byers; S. Skillman; C. Hepburn
- Year: 2021
- Link/Source: 10.1038/s41586-021-03957-7 — PV Labels — Code Repo
- Main objective of the paper: To provide a global inventory of commercial, industrial, and utility-scale PV installations ($\geq 10kW$ nominal generation capacity)

- Methodology used: Machine Learning pipeline (series of CNN + RNN models), OpenStreetMap annotations, heuristic filters, negative sampling (non solar panel objects)
- Number of annotations: 68,661 facilities [36,882 (Sentinel-2), 38,541 (SPOT)]
- Date range for annotations: 2016/06/01 - 2018/09/30
- Annotation locations: Global (131 countries)
- Key findings or contributions: The dataset expands previous publicly available data by $> 4x$. Provides an estimate of global installed generating capacity: $423(\pm 75)GW$. Mentions importance of spectral signature of PV panels and extraction of spectral features. Provides implementation repo. "The pipeline has two stages: an initial global search designed to maximize installation recall, followed by a process to remove false positives and estimate installation dates."

5.3.3 2020-UK-Solar-PV

- Title: "A harmonised, high-coverage, open dataset of solar photovoltaic installations in the UK"
- Authors: Dan Stowell; Jack Kelly; Damien Tanner; Jamie Taylor; Ethan Jones; James Geddes; Ed Chalstrey
- Year: 2020
- Link/Source: 10.1038/s41597-020-00739-0 — PV Labels — Code Repo
- Main objective of the paper: To create an open geographic data source for solar PV, suitable for intra-nation (UK in this case) analysis using machine vision and PV forecasting.
- Methodology used: OpenStreetMap, Crowdsourcing, deduplication via spatial clustering
- Number of annotations: over 260,000 (over 255K separate installations; 1067 large solar farms)
- Date range for annotations: Data was collected up to September 2020
- Annotation locations: United Kingdom
- Key findings or contributions: It includes a large number of small-scale domestic installations, which were typically poorly documented. Provides detailed metadata and location geometries. Discusses challenges of data reconciliation and deduplication which is relevant to our work that will merge multiple datasets. Includes a GUI for data visualization and validation which will likely be relevant or useful for our work

5.3.4 2023-US-large-PV-EIA

- Title: "Georectified polygon database of ground-mounted large-scale solar photovoltaic sites in the United States"
- Authors: K. Sydny Fujita; Zachary H. Ancona; Louisa A. Kramer; Mary Straka; Tandie E. Gautreau; Dana Robson; Chris Garrity; Ben Hoen; Jay E. Diffendorfer
- Year: 2023

- Link/Source:
  10.1038/s41597-023-02644-8 — PV annotations
- Main objective of the paper: To develop a comprehensive, publicly available georectified dataset of ground-mounted large-scale solar photovoltaic (LSPV) facilities in the US.
- Methodology used: Georectification of PV facility coordinates from EIA data. Used high-resolution aerial imagery to validate facilities and digitize location polygon. QA/QC by human annotators. Facility metadata was attached to geometries.
- Number of annotations: 3,699 ground-mounted LSPV facilities
- Date range for annotations: Vector geometries with no attached imagery. Facilities became operational between 2018 and 2023.
- Annotation locations: Continental USA
- Key findings or contributions: N/A

5.4 2024-LSTM, Sepsis, PPG [?]

Example of the subsection title: "2024 LSTM, Sepsis, PPG", which is a shortened version of: "2024 LSTM Model for Sepsis Detection and Classification Using PPG Signals."

In this report, each paper must fit within one page! I know that reviewing a paper could take more space, but for that, use a separate document.

I intentionally use BLUE to capture attention, RED for negative or unexpected results/data, and GREEN for positive ones.

5.5 20xx ASDF

A monthly report usually includes three news articles. Two is acceptable, four is good, and more than six is excellent.

6 Conclusions/Discussion/Future Work

Summary of the most relevant findings and complications, potential applications and limitations, and next steps in the research.

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