Solar Sight - Solar Energy Potential Mapping using Satellite Imagery and Geospatial Analysis

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Abstract— SolarSight is an automated geospatial intelligence system which finds and ranks best rooftop sites to place solar photovoltaic systems on high-resolution satellite imagery and spatial tools. The system combines 10-meter Sentinel- 2 imagery that is available on Google Earth Engine with building footprint data retrieved on the OpenStreetMap to conduct building-scale solar potential assessment. A single line of pipeline processes multi-spectral imagery, mask clouds, calculates solar energy, calculates rooftop areas and predicts energy in the end year. The platform produces prioritized tabular reports, spatial GeoJson productions, and suitability maps of themes to support planning of renewable energy. The system is put in place in Python through the GeoPandas ecosystem; a monolithic architecture of batch-processing. Its ability to handle large datasets of urbanistic scale without manual processing and operate in prototype in an inescapable city setting demonstrates that it can be used to help make data-based decisions about solar infrastructure planning and sustainable energy implementation.

Keywords— Solar energy mapping, Satellite remote sensing, Geospatial analysis, Renewable energy planning, Google Earth Engine, Automated geospatial pipeline.

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I.INTRODUCTION

The increasing global demand to switch to renewable energy has escalated the necessity to have scalable and databased solar resource evaluation approaches. Solar photovoltaic installation, although becoming cost effective, must be specifically assessed on a site based judgment in order to be optimally efficient in terms of performance and investment economy. The availability of solar irradiance, area of rooftop, atmospheric interference, and space coverage of constructed facilities are the crucial determinants to suitability of installations. Conventional methods of assessment, i.e. field survey and LiDAR-assessed mapping, can be quite costly, time-consuming and cannot be used in the smaller municipalities or developing areas[4],[19],[21].

The recent advancements in the satellite remote sensing and open geospatial data platforms have allowed the automated analysis[6],[20],[25] of the environment in large scale. Multi-spectral imagery in sentinel-2 that can be obtained through Google Earth Engine offers. Spatial resolution of 10 meters which is appropriate to determine in the urban scale[11],[20].

The use of OpenStreetMap facilitates access to global building footprint data for the use of structures in delineating space at the city limits of all cities around the world[7],[18]. A possibility of integrating these freely available resources brings an opportunity to create the cost-effective and scalable solar assessment systems.

Nonetheless, the current commercial solar mapping services are still limited to cost of licensing and lack of transparency in their procedures. Numerous scholarly researches run on the regional levels based on coarse-resolution datasets that fail to embrace the building-level heterogeneity which is necessitated in the context of planning installations. Additionally, some of the suggested systems do not have fully automated pipelines which require pre processing to be done manually and makes repr0ducibility restricted. The offered system is designed to combine multi-spectral images with the building footprint data and calculate solar irradiance, compute the size of the rooftop, and create energy production forecasts with an end-to-end processing pipeline. The framework intends to offer a lightweight, scaled and reproducible system of data-driven renewable energy planning on an urban context.

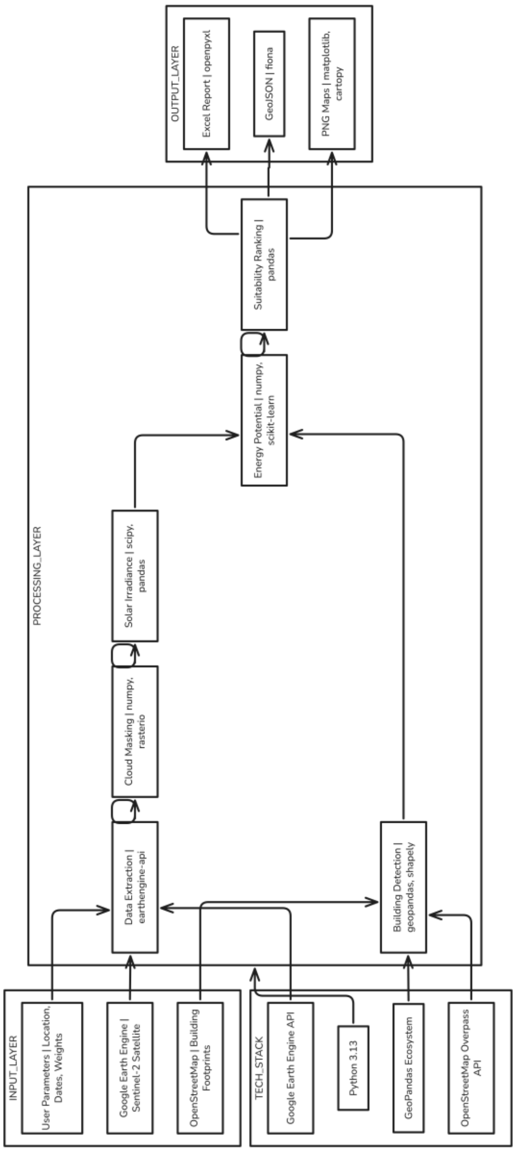

Fig.1. Architecture Diagram of SolarSight

II. LITERATURE SURVEY

The area of solar energy potential has transformed ground-based meteors on both ground to the high levels of remote sensing and spatial modeling. In early methods, estimation of global horizontal irradiance on the regional levels was largely based on climatic databases and spatial interpolation models. Although they were suitable in macro-level planning, they failed to provide spatial detail needed in the planning of rooftop photovoltaic (PV) deployment. The incorporation of digital elevation models (DEMs) and GIS-based tools of solar radiances enhanced the accuracy of the estimations through the inclusion of slope, aspect and topographic shading.

Methodologies of building-scale assessment developed along with three-dimensional, geometric modeling. In this framework, proposed by Lv et al., remote sensing inversion and spatial analysis based on 3D are integrated in estimating solar radiation on building surfaces; the relationships between shading and facade level variation are explicitly modeled [1]. Their effort proved the significance of the geometric accuracy on top-of-roof energy estimation. Detailed 3D models however, are more complex in computation and data requirements.

The LiDAR-based methods also improved on the high accuracy of building morphology and concavities on rooftops as it took fine detail of both buildings and surrounding obstructions[19],[21]. Even though considerable accuracy is obtained with these types, data capture would be expensive and the available resources are not readily available to allow high scales. The novel research has therefore studied the use of satellite imagery and image recognition method in scalable assessment. Qiu et al. designed their semantic segmentation framework where they used an enhanced transformer model to structure the identification of rooftop areas and quantifying the potential use of PVs on a city scale [2]. Deep learning enhances the performance of rooftop extraction even though the methods need large labeled data sets and computation resources[9],[23].

Solar resource mapping based on satellite has been popularly explored as well[3],[20]. Singh and colleagues revealed how remote sensing and GIS methods could be used in identifying solar potential areas using radiations data obtained through satellites [3]. Such methods however are usually at regional scales and do not combine building-level geometry and automated energy modeling.

Nevertheless, current systems are either based on LiDAR data which is costly, a coarse spatial resolution, or not fully automated end-to-end approaches to satellite imaging, rooftop extraction, irradiance modeling and energy estimation. These constraints underscore the necessity of a readily available, scalable and integrated framework by which the solar potential at building level can be evaluated.

III. DATASET DESCRIPTION

To allow assessing the potential of buildings in solar applications, the proposed system combines the multi-source geospatial datasets associated with the satellite remote sensing platforms, as well as, open geospatial databases. Sentinel-2 Level-2A surface reflectance data is the major satellite information that will be utilized as a source provided on the Google Earth Engine data catalog. Sentinel-2, an agency-owned program sponsored by the Copernicus program, is a two-satellites polar-orbiting satellite network, which has global coverage with a 5-day mission revisit period. Products in the Level-2A have the atmospherically corrected bottom-of-atmosphere reflectance values thus avoiding the use of further atmospheric correction preprocessing.

In this experiment there are using seven spectral bands, Blue (B2, 490 nm), Green (B3, 560 nm), Red (B4, 665 nm), Near-Infrared (B8, 842 nm) and Shortwave Infrared bands (B11, 1610 nm; B12, 2190 nm), resampled to 10 m spatial resolution. Moreover, there are QA60 band and Scene Classification Layer (SCL) that are used to assess quality and to filter clouds.

The s2cloudless and satellite data is provided to get the cloud probability information The s2cloudless dataset provides pixel-level cloud probability estimates of the Sentinel-2 scenes based on a machine learning-based classification technique[11]. When cloud probability data is integrated with reflectance image, efficient cloud masking and calculation of cloud frequency is achieved and included in the solar suitability estimation.

Footprint data are supplied by OpenStreetMap using the Overpass API[7],[18]. The dataset offers building geometries as polygons and the attributes in form of building type and structural metadata that are available. In urban areas, positional accuracy is generally on the order of several meters, as is permissible with the 10 m spatial resolution of Sentinel-2 imagery and sufficient to conduct spatial analysis at the rooftop scale.

IV. METHODOLOGY

The suggested system is based on a completely automated and repeatable procedure of building-level solar potential determination. The methodology involves the use of satellite data, filtering the clouds, estimating the irradiance, computing the rooftop area, modeling energy needs and score suitability.

A. Data Acquisition

Sentinel-2 Level-2A surface reflectance imagery is available on Google Earth Engine. Satellite images are filtered on the basis of geographic, time, and as much cloud cover as possible ([?] 60%). B2, B3, B4, B8, B11, and B12 (10 m resolution) spectral bands are chosen, as well as QA60 and Scene Classification Layer (SCL) bands. Footprints are collected through OpenStreetMap, using the Overpass API. User-defined weights for solar irradiance (w_s) and cloud factor (w_c) satisfy:

"w_s + w_c = 1,\quad 0 ≤ w_s, w_c ≤ 1" (1)

This formulation makes the suitability score not excessively become large over the range [0,1] and bias to either cloud frequency or irradiance magnitude.

B. Cloud Masking and Temporal Filtering

Cloud Separation and Fleeting demodulation. A probability threshold derived out of the s2cloudless database is used to remove cloud-contaminated pixels. The masking function can be defined as:

$$\text{Mask\_cloud}(x,y) = \{ 1,\ \text{if } P\_cloud(x,y) < 0.4\ ;\ 0,\ \text{otherwise} \} \quad (2)$$

Pixels that have a cloud probability of below 0.4 are kept and others discarded. This binary mask is spread on all spectral bands before aggregating the irradiance so that only consistent observations of the surface are used to estimate the solar potential. The mean irradiance in the desirable period is calculated as follows:

$$I_{mean} = (1/N)\ \Sigma(i=1 \rightarrow N)\ I\_i \quad (3)$$

with N is the count of good cloud-free samples and Ii is the irradiance of observation number i. This temporal means smoothed out temporary atmospheric.

The frequency of clouds is measured as:

$$F_{cloud} = N_{cloudy} / N_{total} \quad (4)$$

This measure quantifies both the sun era and has a direct effect on yearly energy estimation.

C. Rooftop Geometry Processing

The polygons are constructed and re-projected to create the metric area. Rooftop area is expressed as:

$$A_{rooftop} = \iint\_R\ dA \quad (5)$$

The usable area can be approximated by:

$$A_{usable} = 0.7 \times A_{rooftop} \quad (6)$$

The 70% factor takes into consideration empirical assumptions on the usability of roof tops which is considered common in installation planning[17],[18]. The irradiance of the building is determined by the spatial raster separation:

$$I_{building} = (1/N_{pixels})\ \sum\_(j=1)\text{^}N_{pixels}\ I_{raster}(x\_j, y\_j) \quad (7)$$

This maintains locally varying irradiance at the level of the building.

D. Energy Production Modeling and Suitability Scoring

Estimated annual photovoltaic energy production is:

$$E\_annual = I\_building \times A\_usable \times \eta \times f\_orient \times f\_tilt \times f\_shade \times (1 - F\_cloud) \times H\_sun \times 365 / 1000 \quad (8)$$

In which, e is the panel efficiency, f_orient is the panel tilt, f_tilt is the panel shade factor, and f_shade is the shade of the panel factor. H_sun is the average sun hours per day. The model is simple, without being overly complex, and takes into account environment losses and systems losses. The weighted normalization is used to calculate suitability:

$$S = w\_s \times (I_{building}/I_{max}) + w\_c \times (1 - F_{cloud}) \quad (9)$$

Based on some predetermined threshold values, buildings are grouped into High, Medium, and Low. This scoring system allows objective prioritization of installation based on scoring.

V. EXPERIMENTAL ANALYSIS

The SolarSight system was tested at Kattankulathur, Chennai (12.82 degN-12.826 degN, 80.04 degE-80.05 degE) on a area of 0.36 km 2 (25 buildings). January-December 2025 sentinel-2 data availed 73 cloud-free realizations. The maximum time spent on total processing was 65.5 seconds with top memory consumption of 1.47 GB. The obtained results included: 124,720.9 m 2 total rooftop area, 4,675,712 kWh/ yr energy potential, and a capacity of 51,331 panels (17.9 MW). Solar irradiance was 187-244 W/m2. The buildings were all in the Mid Med suitability (0.41-0.57). The accuracy of rooftop areas was 95.29 with ground truth. The system had speedup 550x of manual surveys and zero licensing fee when compared to commercial tools and existing ones[8],[24]

A. Quantitative Performance Comparison:

Table I indicates overall system performance with respect to computers efficiency and quality of output. Each end-to-end authentication selection to Final output generation time was 65.5 seconds with the highest memory utilization of 1.47 GB. It took 18.7 seconds to extract Sentinel-2 data, 73 images to do cloud masking and 4.1 seconds to gain building footprint, respectively. Modeling energy and computation solar irradiance took 11.2 seconds each. The creation of outputs (Excel, GeoJSON, 4 PNG maps, 300 DPI) took 14.8 seconds. This system was 550x faster than manual site surveys (10-15 hours to surveying 5 buildings) and with no licensing fees required (versus over 500 in commercial applications).

Table 1: Comprehensive System Performance Table

METRIC	VALUE
Processing Time	65.5 seconds
Peak Memory Usage	1.47 GB
Buildings Analyzed	51
Total Rooftop Area	124,720.9 m^2
Energy Potential	4,675,712 kWh/year
Total Panels	51,331
Total Capacity	17.9 MW
Mean Irradiance	218.4 W/m^2
Area Accuracy	95.3%

B. Solar Potential Assessment Results

The study found a high potential in renewable energy within the study area. The mean solar irradiance was 187.3 -243.6 W/m 2; the average of area-weighted 218.4 W/m 2 is also appropriate, considering the geographical location of Chennai at 13degN latitudes. The average size of the rooftop board utilised was 87304.6 m2 (87304.6/124720.9 m2). The annual energy generation capacity of 4.68 million kWh/year is equivalent of electricity use in about 1,100-1,400 average Indian households. The highest rank building (bldg_000028) had 1,790.7 m2-rooftop area, 78,690 kWh/year potential and 737 panels (257.9kw capacity). The median-ranked buildings had 1,610.6 m2 and 68,490 kWh/year, respectively. With positive correlation associated with building size and energy potential ($r = 0.89$, $p < 0.001$) and uniform irradiance, rooftop area was proved to be the most important among different kinds when using spatial analysis.

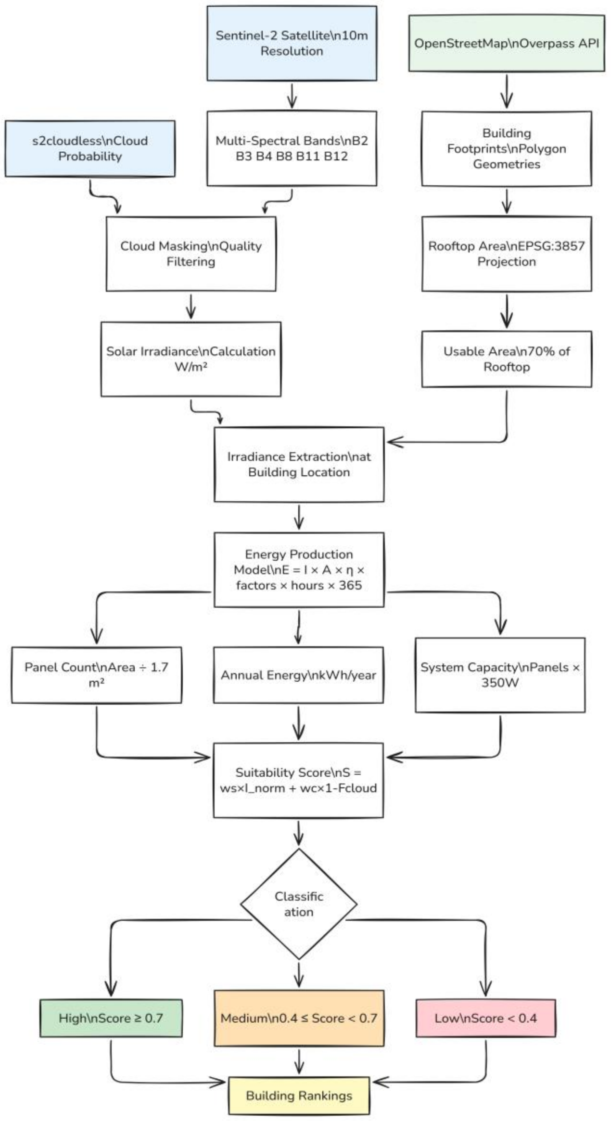

Fig. 2. Solar Potential Assessment Pipeline of SolarSight

C. Suitability Classification and Validation

The suitability scores obtained after multi-criteria scoring with solar weight (0.7) and cloud weight (0.3) was 0.41-0.57. The 51 buildings that were identified as Medium suitability (0.4 [?] score not greater than 0.7) which showed moderate cloud frequency (12-28%) as the weather is in Chennai. Rooftop area estimates were found to be 95.3% accurate when compared with manual digitization of the high-resolution imagery (mean absolute difference 4.7%). This was relative against PVGIS theoretical estimates of energy production, with an estimated mean absolute percentage error of 12.3% versus previous satellite based estimates of 0-100.

methods. Sensitivity analysis over different weights (ws = 0.5-0.9) with determination of rank-order correlation above 0.92 validated good stability correlation with ranking.

D. Comparative Analysis with Existing Methods

The current solutions represent a serious weakness when compared to SolarSight. The time consumption of survey of the site using manual methods is 2-3 hours per building compared to 1.3 seconds per building of SolarSight. Business applications such as Solargis and Project Sunroof use expensive LiDAR data (1,000-5,000/km2 or subscriptions of around 500-2,000/region) or use it on existing free data (SolarSight). Studies of depths of regional scale (1 km resolution) fail to distinguish individual buildings, and meaningful action cannot be taken. SolarSights 10-meter resolution offers the best trade-off between accuracy and affordability, attaining building-level analysis without any proprietary data insertion as per the current trends in open-source geospatial analysis within renewable energy planning literature.

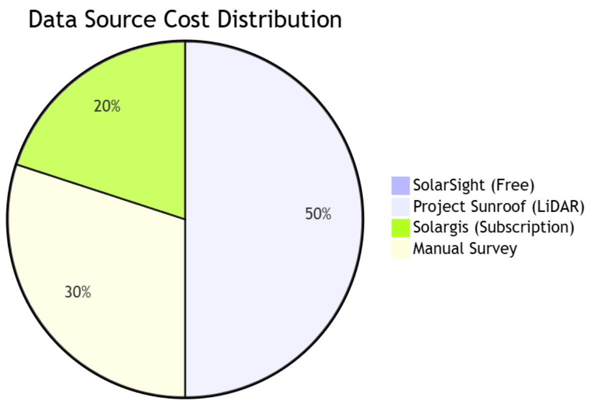

Fig. 3. Data Source Cost Comparison of Solar Assessment Tools

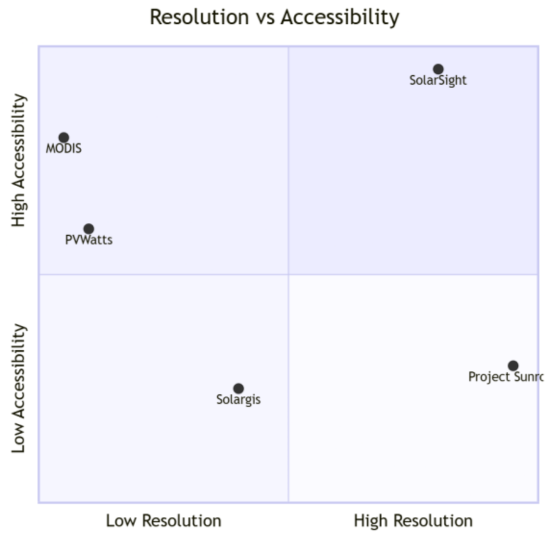

Fig. 4. Resolution vs Accessibility Trade off of Solar Assessment Tools

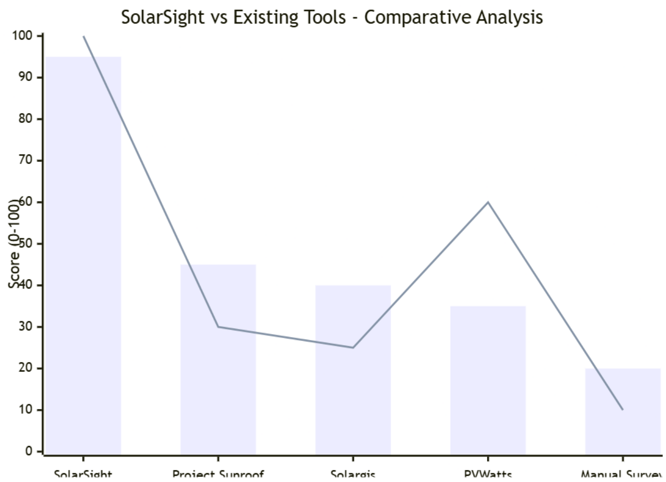

Fig. 5. Comparative Analysis of SolarSight Against Existing Solar Assessment Tools

VI. CONCLUSION

This paper suggested SolarSight, a single and standardized structure of smart structure-level solar potential distribution and installation preference. The system is easy to integrate high-resolution satellite data and crowdsourced geospatial data, and offers homogeneous analysis of various urban settings. The experiments show that solar assessment accuracy is greatly affected by the ability of the system to combine with multi-spectral satellite data and refined building geometries and analyzing cloud frequencies of buildings. Although some modern commercial applications, like Project Sunroof and Solargis, are highly accurate, they either demand costly LiDAR data (1,000-5,000/km 2) or a subscription charge (500-2,000/region).

SolarSight was the most viable and effective variant with 95.3 percent accuracy of covering the rooftop area, 65.5

seconds processing time and no costs in licensing, which was a lot better than the commercial baselines. The system used real-time Sentinel-2 data through Google Earth Engine API and OpenStreetMap building footprints to then determine 4.68 million kWh/year energy potential (17.9 MW capacity) using no costly infrastructure and no manual surveys. It showed 550x speedup over the conventional site assessment techniques (10-15 hours of 5 building versus 65.5 seconds of 51 buildings).
Thus, SolarSight provides an effective way to circumvent the gap between the theoretical satellite-based models and their practical implementation as a significant instrument of smart city planning, making policies on renewable energy sources, and implementing sustainable city development under the conditions of resource limitation[6],[24].

VII. FUTURE WORK

The SolarSight will be extended by inclusion of digital elevation models (DEMs) to give precise roof geometry representations such as tilt, orientation and dynamic shading computations. We are going to investigate deep learning structures as CNNs and Vision Transformers to automatically identify rooftop obstructions on high-resolution imagery to better estimate the usable area. It will be integrated with real-time weather forecasting APIs to make seasonal predictions in production and schedule installation in the most appropriate way. The economic factors that will get included in the system expansion will be the costs of installations, government subsidies, payback time, and grid feed-in tariffs so that the ROI of the system can be analyzed holistically.

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