Advances in Applied Energy 10 (2023) 100129

Contents lists available at ScienceDirect

Advances in Applied Energy

journal homepage: www.elsevier.com/locate/adapen

GIScience can facilitate the development of solar cities for energy transition

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ARTICLE INFO

Keywords:
Geographical information science
Geospatial technologies
Solar energy
Energy transition
Distributed energy systems

ABSTRACT

The energy transition is increasingly being discussed and implemented to cope with the growing environmental crisis. However, great challenges remain for effectively harvesting and utilizing solar energy in cities related to time and location-dependant supply and demand, which needs more accurate forecasting- and an in-depth understanding of the electricity production and dynamic balancing of the flexible energy supplies concerning the electricity market. To tackle this problem, this article discusses the development of solar cities over the past few decades and proposes a refined and enriched concept of a sustainable solar city with six integrated modules, namely, land surface solar irradiation, three-dimensional (3D) urban surfaces, spatiotemporal solar distribution on 3D urban surfaces, solar photovoltaic (PV) planning, solar PV penetration into different urban systems, and the consequent socio-economic and environmental impacts. In this context, Geographical Information Science (GIScience) demonstrates its potent capability in building the conceptualized solar city with a dynamic balance between power supply and demand over time and space, which includes the production of multi-sourced spatiotemporal big data, the development of spatiotemporal data modelling, analysing and optimization, and geo-visualization. To facilitate the development of such a solar city, this article from the GIScience perspective discusses the achievements and challenges of (i) the development of spatiotemporal big data used for solar farming, (ii) the estimation of solar PV potential on 3D urban surfaces, (iii) the penetration of distributed PV systems in digital cities that contains the effects of urban morphology on solar accessibility, optimization of PV systems for dynamic balancing between supply and demand, and PV penetration represented by the solar charging of urban mobility, and (iv) the interaction between PV systems and urban thermal environment. We suggest that GIScience is the foundation, while further development of GIS models is required to achieve the proposed sustainable solar city.

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https://doi.org/10.1016/j.adapen.2023.100129
Received 31 December 2022; Received in revised form 7 February 2023; Accepted 22 February 2023
Available online 25 February 2023

1. Introduction

During the past century, fossil fuels have been used heavily as the primary engine for the global industrial revolutions, which however has caused serious environmental problems, such as air pollution [1], global warming [2], and the urban heat island effect [3], that severely threatens the ecological system of the earth. It was suggested that to limit global warming at 2 °C with a 50% probability in the 21st century, the total carbon emission should be limited to 11 Gt CO_2 between 2011 and 2050. However, gas emissions from the consumption of conventional fossil fuels have already taken approximately three times of the designated number [2]. It was also suggested that about 33% of the oil reserves, 50% of gas reserves, and 80% of coal reserves should not be used by 2050 to achieve the target of the Paris Agreement limiting global warming below 2 °C [2]. In this circumstance, there is an increasing demand for facilitating the wide utilization of renewable energies to mitigate climate change.

To cope with these challenges, the international community has promoted energy transition to renewable energy sources to reduce dependency on conventional energy sources [4–6]. One study emphasized that time matters for smartly balancing variable renewable energy supplies, maximizing the benefits of energy consumers, and optimizing the integration of energy systems [4]. To achieve this, it is imperative to (i) understand the characteristics of intermittent renewable energy and forecast the electricity production related to the market; (ii) build resilient energy systems that are capable of coping with extreme weather conditions; (iii) predict the production and supplement of renewable energies; (iv) model the time-dependant energy consumption associated to the load profiles of the real electricity demand; (v) integrate energy storage to enhance the flexibility of prosumer benefits; and (vi) propose robust control and effective management of the renewable energy systems to dynamically balance supply and demand [4]. As one of the most popular renewable energies, solar energy has attracted much attention in recent years and solar farming has experienced booming development, resulting in the rising demand for adopting solar PV systems in cities since there is a consistent increase in solar photovoltaic (PV) transition efficiency and decrease of the purchase cost [5,6].

Although there is great potential to widely use solar energy since new generation of PV modules are keeping updated and it is clean and abundant on the majority of the earth's surface, effectively utilizing solar energy is still difficult due to its intermittent characteristics mainly caused by the obstacle of the atmosphere and variable weather conditions, which makes it even harder to instantly meet fluctuating load demands. With the rapid development of geospatial technologies in recent years, such as Geographical Information Science (GIScience) and geographical artificial intelligence (GeoAI), it is possible to incorporate the simulation of dynamic geographical environments and spatiotemporal geographical evolutions into a digital city model [7–9], which provides new opportunities to address the challenges in modelling, analysing, and balancing the heterogeneous relationship between solar supply and energy demand over time and space. The major contributions of this article include: (i) proposing a new concept of sustainable solar city with six interconnected modules to meet the new demands on dynamic balancing between heterogenous supply and demand; (ii) designing a system architecture orientated in GIS technologies for implementing the proposed solar city; (iii) analysing the fundamental roles of GIScience in interdisciplinary research for the solar-city development; and (iv) reviewing relevant studies and discussing future GIS-based research to achieve such version.

The remainder of this paper is organized as follows. Section 2 reviews the development of a solar city and proposes the concept of a sustainable solar city to meet the new demand for dynamic balancing between supply and demand. Following the system architecture of a sustainable solar city, Sections 3, 4, 5, and 6 respectively discuss the achievements and challenges in developing a sustainable solar city from the perspective of spatiotemporal data production, modelling, analysis, and optimization. Finally, Section 7 presents the conclusion. The list of nomenclatures is presented in Table 1.

Table 1
List of nomenclature.

No.	Full notation	Abbreviation
1	Geographical Information Science	GIScience
2	Geographical Artificial Intelligence	GeoAI
3	Three-dimensional	3D
4	Light Detection and Ranging	LiDAR
5	Unmanned Aerial Vehicle	UAV
6	Meteorological/Statistical	METSTA
7	Support Vector Regression	SVR
8	Random Forest	RF
9	Multi-Layer Perceptron	MLP
10	Gradient Boosting Machine	GBM
11	Level-of-Detail	LoD
12	Convolutional Neural Networks	CNNs
13	Electric Vehicles	EVs
14	Vehicle-to-Grid	V2G

2. Conceptualization of a solar city

2.1. Development of a solar city

Four decades ago, people began to postulate that a "solar city" could be achieved when 100%, 59.7%, and 18.2% of the energy demand from residential, commercial, and industrial systems could be supplied by onsite solar collection [10], which could be one of the earliest studies about solar cities. In 1998, Couret et al. [11] conceptualized a solar city as an integration of a habitant city, a cultural city, and a sustainable city that can preserve natural resources, promote energy conservation, enable socio-economic sustainability, and optimize urban planning, with an adaption of appropriate technology. In 2006, a future solar city was proposed with three-dimensional (3D) characteristics that incorporate new industry, energy innovation, and eco-culture, which aims to decrease carbon footprint, develop renewable energy, and pursue economic development [12]. These propositions show that the development of solar cities requires interdisciplinary knowledge. Vanderburg emphasized in [13] that a knowledge infrastructure is needed to guide the evolution of the urban habitat toward solar cities, which requires the introduction of a preventive orientation into each relevant area of specialization, e.g., architecture, urban planning, civil engineering, urban management, and politics. In recent years, the concept of solar cities has been further developed. Beatley [14] proposed the vision of a solar city that can produce energy, food, and materials and achieve carbon neutrality by incorporating solar energy into designing and developing green infrastructure, and Scheer [15] believed that solar cities help transform the global energy supply to the reconnection of local energy generation and use from technical and social logic perspectives. The previously proposed solar cities are capable of powering cities in many ways that can make positive effects on socio-economy and environment, while it lacks the flexibility and precision in dynamically handling mismatched loads between supply and demand.

2.2. Definition of a sustainable solar city

To meet the new demands for energy transition with the capability of handling dynamic balance, we refine and further enrich the concept of solar cities. We define a solar city as a sustainable power system that collects, stores, and utilizes solar energy to power a variety of urban systems efficiently and smartly, resulting in an increase in solar penetration, an improvement of socio-economic conditions, and the creation of a liveable urban environment. We propose that a solar city can be built by integrating hierarchical and interconnected modules (Fig. 1), including

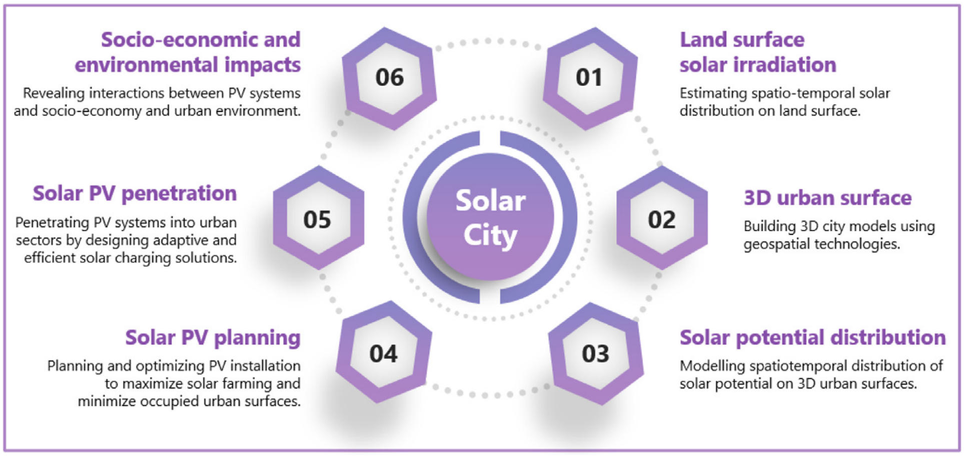

Fig. 1. The concept of a solar city consisting of six integrated modules.

(i) *land surface solar irradiation* that estimates spatiotemporal solar distribution on the flat land surface, which is significantly affected by unstable weather and stable climate possibly with seasonal variations,
(ii) *3D urban surface* that is presented by 3D city models, containing but not limited to major geo-objects, such as natural terrain, buildings, and vegetation,
(iii) *solar potential distribution* that models the spatiotemporal distribution of solar potential on 3D urban surfaces,
(iv) *solar PV planning* that plans and optimizes PV installation to maximize solar farming and minimize occupied urban surfaces to meet the electricity demand,
(v) *solar PV penetration* that allows PV systems to power various urban systems by designing adaptive and efficient solar charging and storage solutions, and
(vi) *socio-economic and environmental impacts* that reveal the consequent interactions between PV systems and socio-economy and urban environment.

In the figure, modules 1 to 3 present the electricity supply capability in different spatial and temporal scales, such as hourly, monthly, or annual PV electricity generation; modules 4 and 5 demonstrate solar harvesting to meet real electricity demand by various urban systems; module 6 reveals the impacts of a developed solar city. It is noted that the solar city is constrained by an independent and dynamic urban environment. However, this does not mean that a solar city will be completely self-sufficient by only harvesting solar energy. We suggest that the utility-scale solar PV plants outside the city are also essential to generate a great amount of electricity. Nevertheless, harvesting solar energy in the local city has two major advantages, which can avoid large energy loss because of long-distance transmission, and easily adapt to complex urban systems, creating additional social and economic impacts. For instance, building-integrated PV sun shading boards can (i) cool down indoor temperature and thus reduce air conditional usage, (ii) generate a certain amount of electricity to power buildings, and (iii) be useful for architectural aesthetics. On the other hand, we suggest that the current energy saving because of solar farming can be absorbed by future urban growth with larger energy demand. However, in the future perspective, urban growth both vertically in height and horizontally in the area can increase the installed capacity of PV arrays, and PV transition efficiency will also be increased because of the development of material engineering. This will make an increased reduction of conventional fossil fuel consumption.

2.3. System architecture of a sustainable solar city based on GIS technologies

According to this new definition, electricity supply and demand are two major components in a solar city (Fig. 2). Specifically, the supply side includes a series of models that estimate land surface radiation based on the clear-sky radiation with the influence of multiple factors (i.e., location, cloud cover, terrain variation, and 3D buildings), which allows the estimation of PV electricity generation through the planning and installation of PV systems, followed by power transmission and power storage. Meanwhile, the demand side refers to the electricity demand from various urban systems, such as electricity consumption from buildings and charging demands from e-vehicles and e-scooters, which is affiliated with the consequent effects on socio-economic development and urban environmental improvement.

The heterogeneous relationship between demand and supply requires dynamic balancing over time and space to build an adaptive and resilient energy system. To achieve this, GIScience enriched by multi-sourced spatiotemporal big data is the foundation in constructing a sustainable solar city. As shown in Fig. 2, GIScience with the support of GeoAI presents its powerful capability in

(i) *multi-sourced spatiotemporal big data production* to support the construction of a solar city by seamlessly coupling with geospatial technologies (e.g., remote sensing, surveying, urban sensing, LiDAR scanning, and UAV monitoring), leading to the creation of datasets, such as land surface solar irradiation maps to determine annual solar potential, 2D rooftop area maps and 3D city models to estimate shadow effects in an urban environment, large-scale PV area distribution maps to estimate life-cycle electricity generation, and roadside noise barrier maps and street-view images to plan suitable locations for PV installation,;
(ii) *spatiotemporal data modelling* to model the time-series distribution of spatiotemporal solar PV potential on 3D urban surfaces, considering the effects of seasonal variation, unstable weather, shadowing from buildings and terrain variation, and multiple reflections between urban surfaces;
(iii) *spatiotemporal data analysis* to identify PV potential locations that are quantitatively large and spatially concentrated, suggesting preferred areas for planning PV installation at solar-abundant locations;
(iv) *spatiotemporal multi-objective optimization* to penetrate PV systems for powering urban systems through spatiotemporal optimization with the development of multi-objective functions (e.g., maximizing solar farming while minimizing PV areas to meet real electricity demand), and estimate its impacts by building interactive socio-

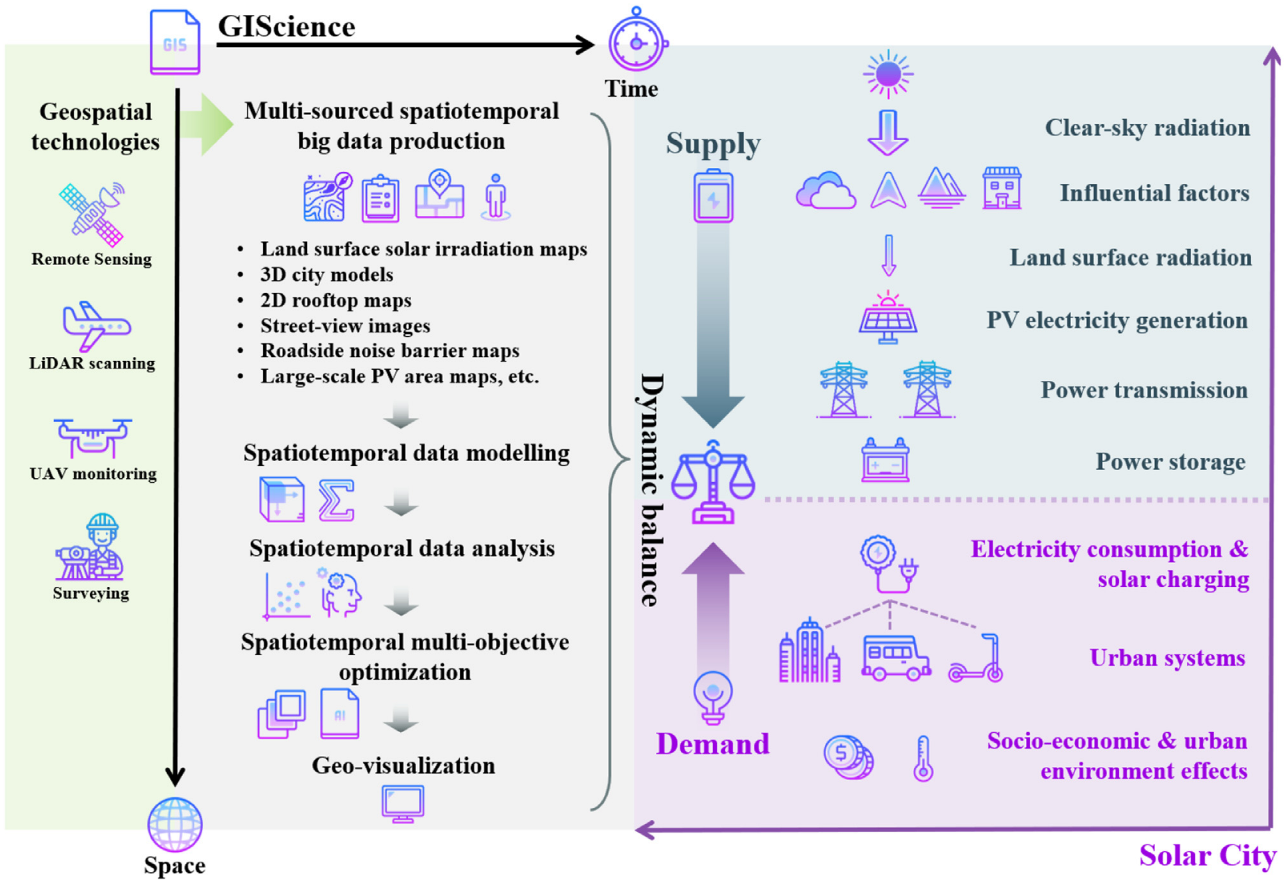

Fig. 2. System architecture of a sustainable solar city.

economic models and urban micro-environment models that are dynamically interacting with the PV systems; and
(v) *geo-visualization* to better understand, plan and develop solar cities.

2.4. The fundamental roles of GIScience in developing a sustainable solar city

Based on the above illustration, we suggest that efficiently powering urban systems with solar energy requires interdisciplinary research to balance between supply and demand over time and space. This, with the distinct characteristics of spatiotemporal heterogeneity, presents the fundamental roles of GIScience in science fusion (Fig. 3).

1 GIScience is the foundation for integrating interdisciplinary research, including but not limited to data science, solar engineering, and system science. This is because GIScience can seamlessly (i) interconnect data science to create and analysis geospatial big data (e.g., using deep learning, computer vision, and surveying to build 3D building models in different Level-of-Details (LoDs)), (ii) incorporate solar engineering (i.e., material engineering to determine PV transition efficiency and electrical engineering to design smart grids) to estimate solar power generation in real geo-environment, and (iii) integrate system science to understand spatiotemporal characteristics of each system with an establishment of professional knowledge to power the system efficiently.
2 GIScience is the key in developing a series of hierarchal models to plan efficient solar farming. This presents the distinctive capability of GIScience on abstracting and modelling geographical phenomena (e.g., estimating solar distribution on 3D urban surfaces), analysing spatiotemporal solar distribution (e.g., identifying quantitatively large and spatially concentrated PV potential areas), and planning solar PV installation (e.g., determining the location, orientation, and installed capacity of PV arrays).
3 GIScience plays an essential role in optimizing spatial-associated PV configurations with an energy storage capability to address the spatiotemporal barriers between supply and demand. It can be used for a variety of applications. Here the applications are related to various urban systems, such as charging e-vehicles, collecting, cleaning, and transporting water, powering indoor air-cooling system, and providing artificial lighting for urban farming. For instance, GIScience can optimize the number and location of distributed PV systems with varying installed capacities, which is essential to charging e-vehicles having heterogeneous electricity demands.

3. Multi-sourced spatiotemporal big data production

This section presents the production of multi-sourced spatiotemporal big data using GIS, Remote Sensing, and GeoAI technologies, which provides fundamental data infrastructure related to solar energy, urban environment, and PV plants (Fig. 4(a)).

3.1. Estimation of land surface solar irradiation

It is important to precisely estimate land surface solar irradiation interfered by the atmosphere, which conclusively determines the total solar potential that can be harvested. Such data can be collected from ground-based weather stations, which are usually updated frequently with high precision. However, sparse observation locations make it difficult to generate spatially continuous solar potential maps influenced by atmospheric conditions, such as clouds and aerosols [16]. To create solar

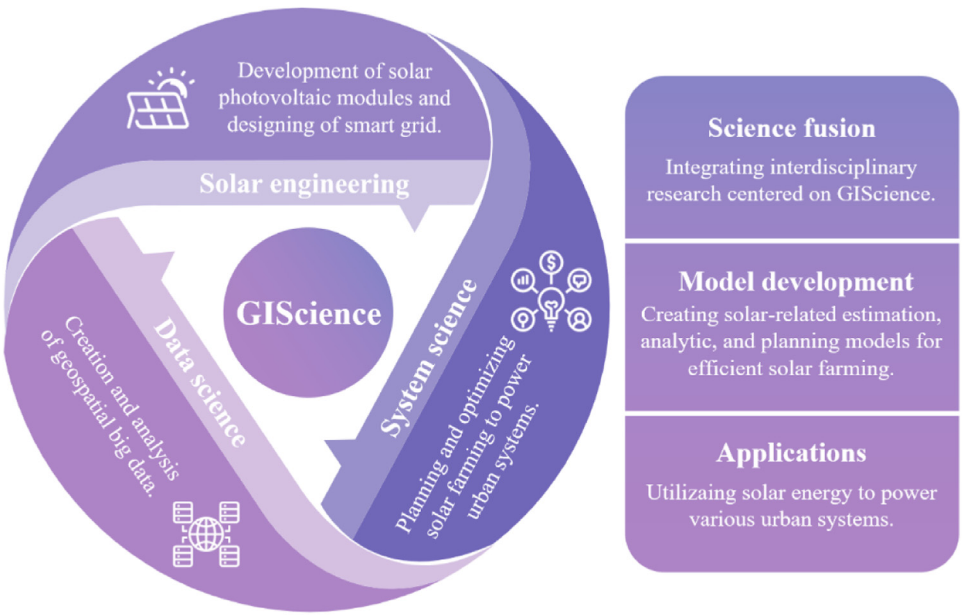

Fig. 3. The fundamental roles of GIScience in developing a solar city.

distribution data with high spatiotemporal resolution over large regions, great efforts have been made during the past two decades [17] that are mainly based on empirical [18,19], physical [20], and machine learning approaches [21–23]. It was suggested that latitude is not the conclusive factor to determine annual solar capacity of a city at a global scale, while urban morphology significantly affects solar capacity of each city [20]. Since empirical models are difficult to be generalized to other regions, physical models were developed and widely used through the modelling of the radiation transmission process, such as the METSTA model [24] and the Bird model [25]. Meanwhile, some studies utilized data acquired from both meteorological stations and satellites [26–28], which was helpful for creating large-scale solar distribution maps, while the temporal resolution was relatively low, limiting the use for near real-time estimation.

Most recently, a series of machine learning networks have been developed for solar irradiation estimation. For instance, Ramedani et al. [29] suggested that Support Vector Regression (SVR) using the polynomial model and radial basis model as the kernel function outperformed fuzzy linear regression for global solar radiation prediction in Iran. Srivastava et al. [30] found that the Random Forest (RF) model obtained the best results in forecasting hourly solar radiation from 1-day-ahead to 6-day-ahead in India, compared to the models of Multivariate Adaptive Regression Spline, Classification and Regression Tree, and Piecewise Linear Functions of Regression Trees. Rabehe et al. [31] concluded that the Multi-Layer Perceptron (MLP) performed better than the Boosted Decision Tree and the combination of the models with linear regressions for the estimation of daily global solar irradiation. Furthermore, Liao et al. [32] estimated seasonal and annual land surface solar irradiation in Australia and China by using four machine learning models, i.e., Gradient Boosting Machine (GBM), RF, SVR, and MLP. Based on the computed clear-sky solar irradiation, cloud optical thickness, and aerosol optical thickness retrieved from Himawari-8 meteorological satellite images, it was found that GBM obtained the highest accuracy and implied that the proposed method was simple and effective for large-scale solar irradiation estimation [32].

3.2. Development of the 3D city model

Solar mapping of urban surfaces, known as “solar cadastre”, has proven to be a promising approach for accurate solar analysis at the building, district, and city levels [33]. However, these approaches have certain limitations, such as using simplistic assessment methods that lead to inaccurate results [33]. Studies on solar energy potential aim at improving the prediction accuracy of solar irradiation on surfaces. Estimating solar potential by simple and general methods is common practice for small-scale roofing installations, but not for solar integrated systems on façades [34]. To guide urban densification processes by optimizing the exploitation of solar energy systems on urban surfaces and simultaneously considering energy demands from buildings, a more advanced approach is needed. Knowledge of solar potential and building energy is crucial to optimise self-consumption in urban areas. Currently, the existing solar cadastres lack a specific focus on urban microclimate conditions and interaction amongst buildings that face complex phenomena (i.e., shadow cast and solar inter-building reflections). Solving complex equations and models for different buildings is helpful for dealing with these interactions. Dedicated tools arose with a modular structure in co-simulation frameworks, and in the specific model, the information exchange at each timestamp allows accounting for the interactions [35]. For instance, in optimization processes at the city scale, such frameworks are used to bring together architectural aspects (geometry), engineering aspects (energy system design), and a part of the microclimate conditions of buildings (local solar potential) [36]. At the city scale, the co-simulation approach allows domain-specific expert tools to work together [36]. Moreover, its efficacy varies considerably due to the accuracy of spatial information available and generated (e.g., satellite data, and data from Light Detection and Ranging - LiDAR), and the used 3D models in different LoDs.

Current developments aim to create more precise information layers to estimate the integration of the solar system on rooftops [37], mostly devoid of building infrastructure (e.g., chimneys, elevator engines) that are common constraints for optimal solar system installation, but also on the non-negligible vertical surfaces (façades) [38]. At high-latitude locations, façades have a high potential to collect sunlight since the sun maintains an optimum angle of incidence for longer, making solar systems’ integration into façades even more favourable than in cities in low latitudes. Moreover, employing vertically mounted solar systems, present a better operating condition for solar systems since they do not accumulate much dust and rarely will be covered by snow in the winter, which brings an increase in solar energy production and more im-

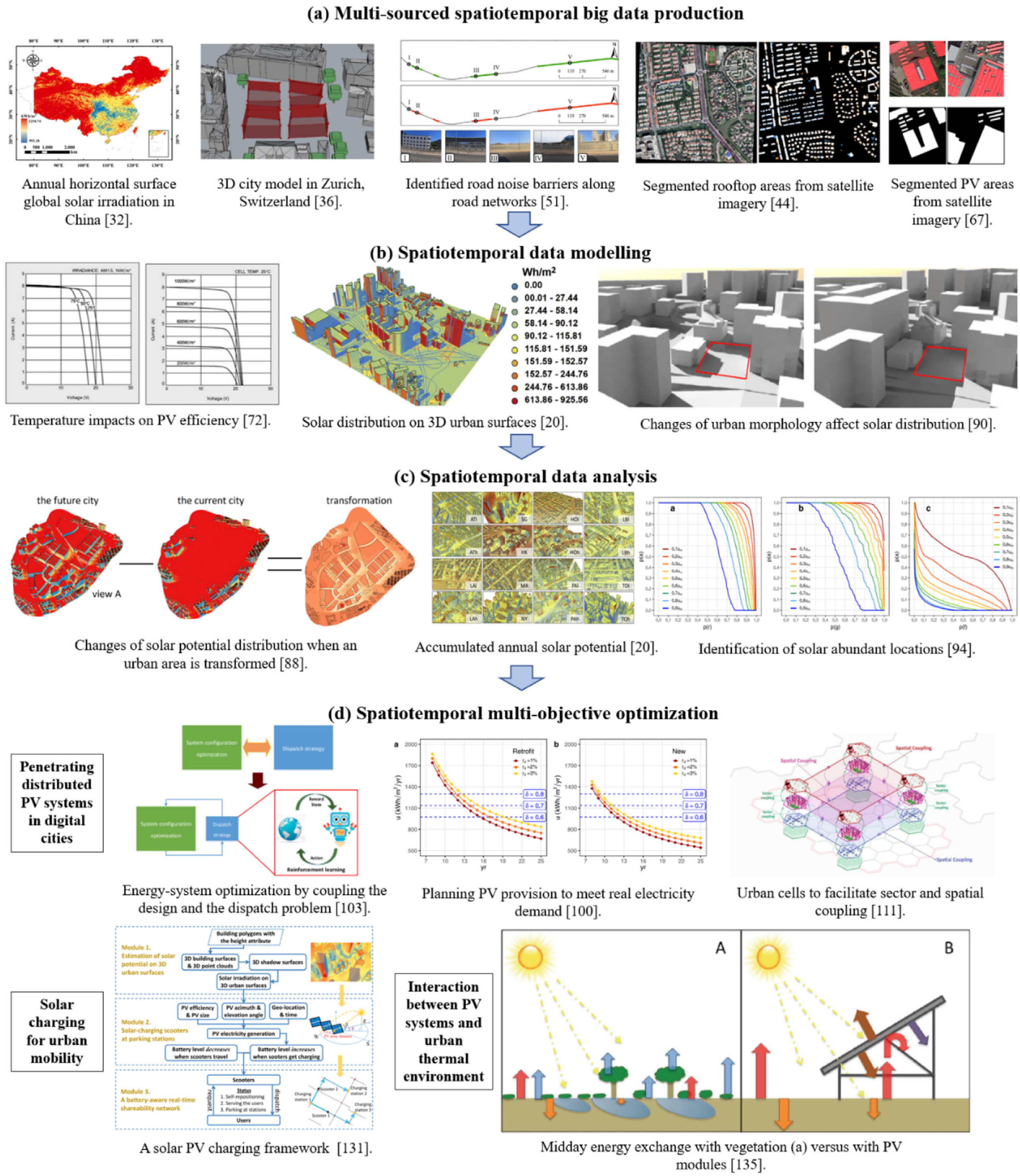

Fig. 4. A hierarchical workflow to develop the proposed solar city. (a) Multi-sourced spatiotemporal big data production. (b) Spatiotemporal data modelling. (c) Spatiotemporal data analysis. (d) Spatiotemporal multi-objective optimizations.

portantly matches with electricity consumption and price peaks. The investigation of such unique opportunities requires combined local research to make solar energy more affordable and accelerate its penetration in countries that are in the far north region. However, assessing solar irradiation on building façades and identify suitable areas of the façades (e.g., unglazed) for solar PV installation is more complex than on rooftops. This requires more advanced solar potential estimation models, considering solar accessibility influenced by urban morphology, LoD3 3D model, and the textures and albedos of the façades. In this regard, the rapid development of 3D scanning methodologies makes a compelling case for a comparison in terms of accuracy before large-scale scanning is undertaken. At the neighbourhood level, there are on the one hand LiDAR-based techniques and the other photogrammetry-based techniques. Recently, LiDAR techniques have received a strong boost, and photogrammetry software used to create 3D city models from collections of overlapping photographs has become readily available (e.g., photo modeller), which makes it possible to build fine-scale 3D city models.

3.3. Segmentation of 2D rooftop areas from satellite imagery

Quantifying the available rooftop area is an important and feasible way to estimate the annual solar PV potential on buildings [39]. However, large-scale estimation of building PV potential is challenging due to the lack of available high-quality rooftop data and insufficient generalization ability of modelling methods [40]. To cope with this challenge, many studies have been devoted to automatically extract building rooftops accurately using remote sensing and artificial intelligence techniques, which have contributed to the development of various generative methods and public datasets [41,42].

At the same time, urban energy studies are moving toward finer-grained simulations that require more granular and precise geospatial data. In contrast to extracting accurate building footprints, some studies have explored finer-grained information about building rooftops [43]. For example, as one of the most advanced image-semantic segmentation networks, Deeplabv3+ was used to segment rooftop areas [44–47]. In addition, roof structure lines are fine-grained elements of the roof that can be delineated from satellite imagery to serve as a reference for the morphology of the rooftop [48]. The roof structure lines can divide the roof into multiple components, which can be further mapped with rich attributes (e.g., slope, aspect, and light intensity) to reflect the detailed features of the roof surface, which is helpful for the optimization of PV installations on rooftops [48,49].

3.4. Detection of roadside noise barriers from street-view images

Additionally, as a type of urban infrastructure in metropolitan regions, roadside noise barriers provide an alternative location for PV installation, expanding limited sites to utilize solar resources in densely populated urban regions, which has received great attention from many nations [50]. Rather than conducting costly and time-consuming road inspections and investigations, studies used street-view imagery to capture roadside noise barriers in Nanjing and Suzhou, China, using deep learning (i.e., YOLO v3) and computer vision techniques [51,52]. As a result, PV panel locations and solar PV potentials can be estimated using the mileage and spatial distribution of extracted roadside noise barriers [52].

3.5. Segmentation of large-scale PV areas from satellite imagery

As PV systems have been installed widely in the past few years, recent studies have focused on extracting installed PV areas from satellite imagery, which provides fundamental datasets for estimating the total installed capacity and PV modules [53], analysing the economic and environmental impacts [54], and guiding PV policy-making [55]. The methods of PV area extraction have been developed using remote sensing image segmentation [56], machine learning [57–59], toward advanced deep learning [60,61].

Some studies have combined object-based remote sensing image analysis and template matching techniques to segment PV areas from very high-resolution aerial imagery [56]. Others have utilized machine learning methods, such as random forests, to extract PV areas from high-resolution aerial imagery [57]. While these approaches can detect most PV areas, they have limitations in segmenting areas obstructed by surrounding environments with similar colors and textures.

To address these challenges and achieve more precise segmentation of PV areas affected by various land covers, researchers have developed new models utilizing Convolutional Neural Networks (CNNs). These models, such as DeepSolar [62], ConvNet [63,64], and U-Net [65]. These models have demonstrated their ability to segment PV areas and create city-level PV maps with satisfactory accuracy. More recently, a different type of CNN, Deeplabv3+, which employs Atrous Spatial Pyramid Pooling, has been used to extract PV areas from satellite images [66], and it was suggested that the original and refined DeepLabv3+ were competitive to U-Net and RefineNet for extracting concentrated and distributed PV areas in Heilbronn, Germany [67] and Jiangsu, China [68]. However, these models face difficulties in obtaining refined and regular boundaries for small and distributed PV modules due to challenges such as an imbalance between positive and negative samples in the imagery, variations in color and texture of PV modules under varying daylighting conditions, and the potential misclassification of geo-objects with similar characteristics to PV modules. Therefore, a more detailed-oriented approach, utilizing geospatial technologies and adapting to the challenges posed by PV module segmentation, is greatly needed.

4. Spatiotemporal data modelling

This section introduces GIS models for accurately estimating spatiotemporal solar PV potential on 3D urban surfaces, which is influenced by the urban thermal environment, unstable weather conditions, and complex built environment (Fig. 4(b)).

4.1. Estimation of PV transition efficiency

With an increasing rate of urbanization, urban surface temperatures keep increasing and extreme heat waves become more and more frequent [69–71]. It was found that temperatures on PV surfaces play a key role in electricity generation. This is because the standard PV electricity transition efficiency is tested at a standard temperature of 25 °Celsius, and with a higher temperature, an increase of 1 °Celsius will decrease the PV efficiency by around 0.5% and PV efficiency can be decreased by 25% under high-temperature environments [72]. Since land surface temperatures in urban areas can reach 60 to 70 °C in the summer noon time [73], it is reasonable to consider that air temperatures or land surface temperatures can significantly affect PV transition efficiency through radiation transfer and surface energy exchange, which, however, has not been fully investigated yet. To tackle this problem, we many utilize geospatial technologies to measure real-time PV efficiency, observe varying temperatures of PV surfaces, quantify dynamic thermal environment, and develop spatiotemporal models to estimate the PV efficiency based on all the influential factors.

4.2. Estimation of solar PV potential on 3D urban surfaces

It is important to accurately estimate the spatiotemporal distribution of solar PV potential to plan PV installation at solar abundant locations and assess the electricity generation of installed PV systems. Previous studies incorporated sky view factors to estimate PV potential along street canyons [74,75], which essentially incorporated shadow effects from surrounding buildings. To assist rooftop PV installation, many studies estimated rooftop PV potential [76–78], in which one estimated the probability distribution of annual cloud cover to generate an annual solar potential map on all rooftops in Hong Kong [16].

Further studies developed physical models to estimate solar potential on façades and the ground [79], or on façades and rooftops [80–83]. For example, Catita et al. developed the SOL algorithm to generate 3D points on façades to present solar radiations [80]. Liang et al. utilized an extension of the 2D r.sun model and the Graphics Processing Unit technique to real-timely visualize irradiations at an instant of time on 3D building surfaces [81,82]. In addition, one study modelled the effect of greenery on the amount of solar energy received on building surfaces, which is vital for some cities where greenery is dominant [84].

A few studies showed the capability of estimating solar irradiation on entire urban surfaces, including rooftops, façades, and ground [85–87]. For instance, the SORAM model used a ray-tracing algorithm to determine whether a 3D ray vector intersects with a voxel and to calculate solar irradiations on building surfaces [85]. In another study, the v.sun module considered the shadow effect caused by surrounding buildings and estimated 3D solar irradiation, which was implemented based on the r.sun model that enables the computation of segmenting 3D vectors to smaller polygons [86]. Similarly, urban surfaces were modelled as 3D point clouds to record and visualize solar irradiations on urban surfaces. To achieve this, the total solar irradiations (i.e., direct, diffuse, and reflective irradiations) were modelled as 3D vectors that intersect with 2.5D building surfaces, resulting in an estimation of shadow effects from all surrounding buildings [20,88].

5. Spatiotemporal data analysis

This section demonstrates the developed GIS models for (i) analysing the effects of urban morphology on solar accessibility based on both the current and the transformed urban environments, and (ii) identifying solar-abundant locations that are favourable for collecting solar energy (Fig. 4(c)).

5.1. The effects of urban morphology on solar accessibility

In this context, the optimal geometry of buildings was determined by considering metrics such as building massing, density, and orientation to provide efficient solar PV planning [89–92]. For example, one study proposed twelve building block configurations and manipulated three geometrical parameters (i.e., the width of streets, the heights of existing and planned buildings, and the massing of buildings) to adjust building layouts and finally obtain an optimal integration [92]. However, an optimal solution proposed in an ideal scenario may not be able to be applied in a real urban environment because building design may be influenced by multiple factors simultaneously, such as noise control, indoor daylighting time, and traffic dispersion. Therefore, understanding the effect of a transformed urban environment on solar accessibility of existing and planned buildings is also imperative when a master plan of buildings is established. This can be achieved by comparing the built environments transformed from the current city to the future city [88,90,93]. On this basis, these studies discussed the changes in solar accessibility on different urban partitions (i.e., rooftops, façades, and ground) when a cluster of new buildings are built up.

5.2. Identification of solar abundant locations

For easy maintenance and efficient solar farming, it is reasonable to install PV modules at locations where solar potentials are quantitatively large and spatially concentrated. To achieve this, one study determined the minimum solar potential to be harvested on each of the urban partition (i.e., rooftops, façades, or ground) and computed the rate of usable area on each 3D urban surface [94]. Then, spatiotemporal data analysis was conducted to summarize the rate of urban surfaces that are equal or larger than a designated usable area during a calendar year. With the variation of the minimum solar potential and the rate of urban surfaces to be used for solar farming, the study drawn continuous curves describing the relationship between the two quantities, which was an effective analysis to assist PV site selection based on the expected electricity generation efficiency and the minimum area to be utilized.

6. Spatiotemporal multi-objective optimization

This section illustrates the GIS-integrated models for the planning of solar PV systems with storage capability in an urban scale, designing solar charging solutions to power e-vehicles and e-scooters, as well as revealing its effects on urban micro-environments (Fig. 4(d)).

6.1. Penetrating distributed PV systems in digital cities

Concepts such as energy hubs and smart microgrids are used to improve the penetration of solar energy within urban areas [95–97]. The optimal design of such distributed energy systems is a challenging task that has been widely discussed in the literature. The process begins with quantifying the energy demand, and the second step is quantifying the PV potential, an extensive task comprehensively discussed in the previous sections. Both demand and PV potential are used for energy system sizing [98]. Many optimization models have been used in the present state-of-the-art to perform design optimization of urban energy systems with solar PV [99].

Most of the recent studies focussed on optimal sizing of solar PV panels along with supporting technologies such as energy storage (e.g., battery banks and H_2 storage), energy conversion devices (e.g., heat pumps), and dispatchable energy technologies (e.g., internal combustion generators, combined heat, and power). These studies focused on the optimal design of building-integrated PV systems and the energy hub, which gradually evolved to the neighbourhood and urban scales [100–102]. Both linear and non-linear optimization methods have been used with detailed techno-economic models. However, grey box and data-driven models are becoming attractive alternatives, especially when considering the complex terrain brought up by the urban context [103]. For instance, reinforcement learning can present the optimal despatch [104] while supervised and transfer learning can be used to move from a cluster of buildings to an urban scale [105,106]. Moving into data-driven models will be a promising direction, which is yet to be fully explored.

Given the ambitious decarbonization targets, urban areas should aim to become self-sufficient, being less dependant on the stable electricity supply provided by the grid [107]. The fluctuations brought by energy demand and solar energy potential cannot be solely buffered using energy storage (both long and short) [108]. The flexibility brought up by building, transportation, and industrial systems needs to play a significant role in this context [109]. Therefore, PV integration needs to be considered along with system coupling. Similarly, large-scale grid integration of PV could lead to destabilizing the electricity grid [110]. Considering both system coupling and spatially associated grid stabilization, energy markets at multiple levels will lead to a complex ecosystem. Therefore, optimizing the integration of PV technologies at the building and neighbourhood scale in such a complex energy ecosystem is a challenging task that cannot be completely handled using state-of-the-art centralized models. Decentralized architectures and hybrid architectures (i.e., hierarchically decentralized superstructures) such as Urban Cells are promising approaches in this context [111]. Considering emerging concepts such as block-chains and the urban Internet of Things, it will introduce more challenges in the future that need to be considered during the system sizing phase [111]. The evolution of energy system optimization models, the introduction of machine learning techniques, and the ever-increasing performance of high-performance computing will help to address the challenges and enable solar cities.

6.2. Solar charging for urban mobility

The primary energy source in the transportation system is fossil fuels, which is detrimental to global environments and climate. Thus, electrification of the transport system is a crucial way to build green mobility. However, charging millions of electric vehicles (EVs) can easily overload the power grid [112], and if the electricity still comes from fossil fuels, it is hard to achieve the anticipated benefits of EVs with a significant reduction of greenhouse gas emissions. To tackle this problem, incorporating EVs with solar (or more broadly renewable) energy provides a plausible way for transforming energy structure in the transportation system and meeting CO_2 emission targets [113]. Therefore, it is greatly needed by cities to mitigate global warming and energy scarcity, showing significant economic and environmental impacts on the industry [114].

EVs can return electricity through discharging to provide demand-responsive services using the vehicle-to-grid (V2G) technology. There are considerable benefits to using such technology with solar PV charging stations. With an optimized charging/discharging strategy, V2G can reduce the possible uncertainty of the PV system [115]. EV charging may induce higher loads to the grid, especially during the daytime, and solar PV provides an option to increase daytime peaking capacity, which is considered a co-benefit [116]. V2G could enhance the service reliability of the grid because these grid-connected vehicles can reduce residual load fluctuation if smart charging is implemented [117]. Also, it was found that coordinated EV charging can effectively reduce voltage unbalance [118].

Solar charging stations can be installed in many areas. Earlier research on PV power generation investigated the effects of home solar charging with EVs [119], and solar charging at the workspace will provide more energy supply during the daytime [114]. Also, installing PV arrays in parking lots would provide solar electricity to many EVs [120–122]. A worthy alternative will be deploying solar charging systems in fuel stations, and this can be exploited as a station-to-grid strategy [123]. While most research focuses on connecting solar charging stations with the grid, the possibility of off-grid standalone charging stations using PV and wind was also explored [124]. PV can also be installed on the roof of vehicles. For example, one study proposed a novel battery/PV hybrid power source for plug-in hybrid electric vehicles, which can provide higher power efficiency and speed [125].

To better incorporate solar charging with EVs, load simulation of EV charging is significant to plan and operate the charging systems. New algorithms were proposed to simulate and optimize the scheduling of EV charging [112,115,126]. A good distribution of public charging stations is crucial for EV operations. How to optimize the distribution of these charging stations is challenging, especially for renewable-powered charging stations [127]. Some recent studies also began to explore the possibilities of integrating solar charging with small form-factor vehicles, like electric scooters and electric bikes [128–131].

6.3. Interaction between PV systems and urban thermal environment

Finally, impact assessments are followed to evaluate the environmental effects of the energy system [132,133]. The production of solar energy in cities reduced the dependency on fossil fuels that can help to mitigate global warming [134]. On the other hand, at the micro spatial scale large solar farms can increase the surrounding land surface temperature and air temperature because the reduced vegetation ecosystem reduced latent heat fluxes and the PV increases the sensible heat fluxes [135]. Another study analysed the impacts of solar farming on the local and micro-thermal environment based on Computational Fluid Dynamics simulation and the results showed that the centre of PV area can reach up to 1.9 °C above the annual average of air temperatures at 2.5 m of the ground [136]. These studies showed that PV systems can increase the air and surface temperature at the micro-scale. This also will make an adverse effect on the PV efficiency. In this scenario, creating or identifying a comfortable urban thermal environment is useful and necessary for optimizing spatial locations of PV systems and increasing PV electricity production.

Conclusion

We suggest that solar PV plays a vital role in energy transition and deep decarbonization of urban energy systems, including building, industrial, and transportation systems. While achieving deep decarbonization is challenging due to the fluctuations brought by land surface solar potential, varying energy demands from different systems, and complex urban morphology that influences the PV electricity generation at the building level. In this paper, we proposed the concept of a sustainable solar city, which makes it possible to address these pressing challenges to facilitate energy transition and combat climate change, leading to the creation of a holistic platform to standardize complex data flows. We expect that the successful development of the concept will benefit many parties, including individuals (e.g., the PV consumers), professionals (e.g., urban planners and policy makers), and operators (e.g., electric power supplies).

The proposed concept and the system architecture reveal that interdisciplinarity collaboration between the fields, such as architecture, urban planning, electric engineering, computer science, and transportation, is needed for developing a sustainable solar city. Nevertheless, we need to notice that GIScience plays a critical role in synthesizing interdisciplinarity and realizing the conceptualized solar city. Meanwhile, the theories and methods of spatiotemporal data modelling should be further developed to improve the capability of GIScience in modelling solar-related geographical evolutions. For instance, new GIScience models are desperately needed to present an invisible urban thermal environment having fuzzy boundaries in space, which dynamically interacts with the PV surface temperatures and thus affects the PV transition efficiency. To conclude, the proposed notion of a solar city is a vision that is expected to become a reality soon, and GIScience, the science addressing the interactions between the environment, people, and sensors, is poised to contribute significantly to the creation of such vision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

No data was used for the research described in the article.

Acknowledgments

All authors sincerely appreciate Michael Goodchild (Emeritus Professor, Department of Geography, the University of California, Santa Barbara, USA) for his constructive comments and valuable suggestions on refining the fundamental roles of GIScience in developing a sustainable solar city.

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