

**OPTIMAL SITE SELECTION FOR SOLAR FARMS
USING GIS-BASED FUZZY MULTI-CRITERIA
EVALUATION (MCE) AND NASA POWER DATA IN
THE GEORGETOWN CONURBATION**

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CONURBATION**

by

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LIST OF SYMBOLS

c_i	Value of cells in the fuzzy standardized layer
°	Degree
°C	Degree Celsius
E	Longitude of the east from Greenwich, England
kWh	Kilowatt-hour
kWp	Kilowatt-Peak
<	Less than
≤	Less than and equal to
λ_{max}	Summation of the products between each element of the priority vector and columns
>	More than
≥	More than and equal to
m	meter
‘	minutes
M	million
MJ	Mega Joules
mm	millimeter
MW	Mega Watt
n	Number of data analyzed
N	Latitude north of the equator
O_a	Average of observed climate data
O_i	Observed climate data
%	Percentage
R^2	Coefficient of Determination
s	second

S_i	Simulation climate data
Σ	Summation
S	Suitability score
$\mu(x)$	Membership value of x
w_i	Weight of each criterion

LIST OF ABBREVIATIONS

AHP	Analytical Hierarchy Process
ANP	Analytical Network Process
ARD	Analysis Ready Data
AUC	Area Under Curve
CR	Consistency Ratio
CSP	Concentrating Solar Power
DEM	Digital Elevation Model
DID	Department of Irrigation and Drainage
DM	Decision Maker
EC	Energy Commission
ELECTRE	Elimination et Choice Translating Reality
FAHP	Fuzzy Analytical Hierarchy Process
FiT	Feed-in Tariff
GHG	Greenhouse Gas
GHI	Global Horizontal Irradiance
GIS	Geographic Information System
GIU	GeoInformatic Unit
GMAO MERRA-2	Global Modelling and Assimilations Office Modern Era Retro-analysis for Research and Applications Version 2
IEA	International Energy Agency
LCOE	Levelized Cost of Energy
LCT	Low Carbon Technologies
LSS	Large Scale Solar
MBE	Mean Bias Error
MCDM	Multi-Criteria Decision Making
MCE	Multi-Criteria Evaluation
MBSP	Majlis Bandaraya Seberang Perai
MetMalaysia	Malaysian Meteorological Department
NASA	National Aeronautical and Space Administration
NCER	Northern Corridor Economic Region
NCIA	Northern Corridor Implementation Authority
NDC	National Determined Contributions

NMBE	Normalized Mean Bias Error
NRECC	Ministry of Natural Resources, Environment and Climate Change
NRMSE	Normalized Root Mean Square Error
NUR	NUR Power
OWA	Order Weighted Average
POWER	Prediction of Worldwide Energy Resources
PPA	Power Purchase Agreement
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
PV	Photovoltaic
RE	Renewable Energy
RMSE	Root Mean Square Error
RI	Random consistency Index
ROC	Receiver Operating Characteristic
ROI	Return on Investment
RPVI	Registered Photovoltaic Investor
SARE	Supply Agreement of Renewable Energy
SAW	Simple Additive Weightage
SESB	Sabah Electricity Sdn. Bhd.
SPPA	Solar Power Purchase Agreement
SSE	Surface Meteorological and Solar Energy
TNB	Tenaga Nasional Berhad
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
UNFCCC	United Nations Framework Convention on Climate Change
US	United States
USA	United States of America
USGS	United States of Geological Survey
USM	Universiti Sains Malaysia
WLC	Weighted Linear Combination

LIST OF APPENDICES

Appendix A Questionnaire to collect experts' opinion for AHP analysis

**PEMILIHAN TAPAK LADANG SOLAR YANG OPTIMAL
MENGUNAKAN PENILAIAN PELBAGAI KRITERIA FUZZY
BERASASKAN SISTEM MAKLUMAT GEOGRAFI DAN DATA NASA
POWER DI KONURBASI GEORGETOWN**

ABSTRAK

Penduduk dunia sedang menghadapi kesan perubahan iklim, sebagai contoh cuaca ekstrem dan peningkatan risiko bencana iklim. Sektor tenaga bertanggungjawab dalam melepaskan 46% daripada CO₂ global, memaksa sektor tersebut untuk memilih tenaga boleh diperbaharui. Mengenal pasti lokasi ladang solar yang optimum adalah penting untuk mencapai Matlamat Pembangunan Lestari (SDG) No. 7, menangani keselamatan tenaga, akses tenaga dan tenaga mampu milik. Walau bagaimanapun, memandangkan tenaga solar sangat bergantung pada keadaan iklim sesebuah lokasi, analisis akan memerlukan sejumlah besar data iklim, yang biasanya merupakan batasan bagi negara-negara membangun seperti Malaysia. NASA Prediction of Worldwide Energy Resources (POWER) menyediakan data iklim yang diperlukan, tetapi, sebelum menggunakannya dalam analisis pemilihan tapak solar, prestasi NASA POWER dalam menggambarkan iklim skala tempatan perlu dinilai. Kajian ini menggunakan model GIS-based fuzzy MCE dan NASA POWER data untuk mengenal pasti lokasi optimal bagi pembangunan ladang solar di Konurbasi George Town di Semenanjung Malaysia Utara. Prestasi NASA POWER data dinilai menggunakan beberapa metrik statistik, termasuk “coefficient of determination” (R), “root mean square error” (RMSE), “normalized root mean square error” (NRMSE), “mean bias error” (MBE), dan “normalized mean bias error” (NMBE). Kemudian analisis “analytical hierarchy process (AHP) digunakan bagi mengenal pasti lokasi yang

berpotensi untuk memasang ladang solar di Konurbasi George Town menggunakan beberapa senario yang berbeza. Penemuan bagi analisis ketepatan, prestasi NASA POWER data dalam menganggarkan data cerapan bagi parameter radiasi solar, suhu maksimum dan minimum adalah baik. Berdasarkan analisis kepekaan, perubahan dalam pemberat kriteria menunjukkan kepekaan model yang terhad terhadap perubahan pemberat justeru, membuktikan kekukuhan model tersebut. Kebolehlaksanaan model GIS-based fuzzy MCE dalam mengenalpasti lokasi optimal untuk ladang solar telah ditunjukkan dengan keluasan bawah lengkungan (AUC) , nilai 0.756 dan 0.738. Model ini mengklasifikasikan 10% daripada kawasan kajian sebagai "amat sesuai" dan 27% daripada kawasan kajian sebagai "sesuai", menunjukkan potensi yang tinggi dalam penggunaan tenaga solar di kawasan kajian. Tiada perbezaan yang ketara dalam klasifikasi kesesuaian antara peta NASA POWER dan data yang dicerap menunjukkan potensi data NASA POWER untuk aplikasi pemilihan tapak. Penemuan kajian ini boleh membantu pihak berkepentingan dalam menyasarkan lokasi yang berpotensi tinggi untuk menjana solar dengan cekap dan mampan di Malaysia.

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ABSTRACT

The global population is experiencing the effects of climate change, such as an increased risk of climate disaster risks and extreme weather events. Around 46% of global CO₂ emissions come from the energy industry. Thus, forcing the sector to opt for renewable energy to reduce emissions. Identifying optimal solar farm locations is vital in achieving the Sustainable Development Goal (SGD) No. 7 targets, addressing energy security, energy accessibility, and energy affordability. However, as solar energy is highly dependent on a location's climate conditions, the analysis would require a large amount of climate data, which is usually a limitation for developing countries such as Malaysia. The NASA Prediction of Worldwide Energy Resources (POWER) provides the required climate data, but before using it in site selection analysis, its ability to estimate local-scale climate data must be assessed. This study uses the GIS-based fuzzy multi-criteria evaluation (MCE) model and NASA POWER data to identify the best solar farm sites in Georgetown Conurbation, Northern Peninsular Malaysia. The NASA POWER climate data is first evaluated using statistical metrics like R^2 , root mean square error (RMSE), normalized root mean square error (NRMSE), mean bias error (MBE) and normalized mean bias error (NMBE). Then, the analytical hierarchy process (AHP) approach was used to identify optimal sites for solar farm installation in Georgetown Conurbation under different scenarios. Results show that NASA POWER's solar radiation, maximum and minimum temperature data performed considerable well in capturing the observation

data. According to the sensitivity analysis, weightage adjustments in the criteria show a limited degree of the model's sensitivity and support for the model's robustness. The feasibility of the GIS-based fuzzy MCE model in identifying solar farms is demonstrated by its area under the curve (AUC) values of 0.756 and 0.738. According to the final suitability map, approximately 10% of the study area was categorized as "highly suitable" for solar farms, while 27% of the study area was classified as "suitable". These findings suggest that the study area exhibits considerable potential for solar energy harnessing. There are no significant differences observed in the appropriateness ratings between the maps produced by NASA POWER and the ground-measured data, suggesting the NASA POWER data may be applicable for site selection purposes. The findings of this study may assist stakeholders in effectively and durably determining the most favorable locations for solar farm installations in Malaysia.

CHAPTER 1

INTRODUCTION

1.1 Background Study

The global average temperature is reported to be higher, approximately 1.1°C, relative to the pre-industrial level (1850 – 1900), termed anthropogenic warming (Allen et al., 2018). The term emphasized that the prevailing cause of the temperature increase is human activities related to fossil-fuel-based material consumption (Fleurbaey et al., 2014). Eyring et al. (2021) have presented evidence that human activities are the main contributors to the warming of the whole global climate system. In recent years, climate-related disasters have threatened human societies and natural ecosystems in several ways, such as increases in frequency and magnitude of droughts, floods, and some other types of extreme weather, sea level rises, and biodiversity loss pressing the global population to take immediate action on climate change (Cubasch et al., 2013; Lee et al., 2022; Mysiak et al., 2016). In response to the issue of climate change, the Parties involved in the United Nations Framework Convention on Climate Change (UNFCCC) have reached a consensus to actively strive towards preventing a global temperature increase that exceeds 2°C above pre-industrial levels. Furthermore, they have committed to making additional efforts to restrict this temperature rise to a more ambitious target of 1.5°C, as outlined in The Paris Agreement of 2015.

In pursuing the ambitious goal set in the Paris Agreement, “[...] Parties to undertake rapid reductions in greenhouse gas emissions (GHG) with the best available science, to achieve a balance between anthropogenic emission by sources and removals by sinks of GHG in the second half of the century, in the context of sustainable development [...]” (UN, 2015). Under this agreement, countries worldwide, pledge and participate in reducing carbon emission to prevent “climate tragedy”. There are several

ways of reducing carbon emissions. First is the compliance model suggested by the Paris Agreement that uses National Determined Contributions (NDC) submitted by each party (UN, 2015). The second method is the Kyoto Protocol, which uses the global carbon trading market as a basis (Michaelowa et al., 2019). Third, the adoption and utilization of international low-carbon technologies (LCT), technologies that emit less carbon compared to conventional technology, including harnessing cleaner energy efficiently (Rai & Funkhouser, 2015).

The importance of solar energy to the Earth's inhabitants and its contribution to forming all energy sources exploited by humankind is well recognized and acknowledged. Furthermore, the considerable prevalence of solar energy, surpassing the Earth's entire energy need by a factor of 10,000, renders it the most viable option among various renewable energy sources due to its cost-effectiveness for humanity on a global scale (De Brito et al., 2013). The use of solar energy for electricity conversion has a long history. The origins of solar photovoltaic (PV) technology, which involves the conversion of solar radiation into electrical energy, can be attributed to the scientific endeavors of Antoine-César Becquerel, a French scientist, during the 19th century (Breeze, 2019). Pioneering commercial solar PV cells in the 1950s, the scientists at Bell Lab successfully invented solar PV cells with an energy conversion of 6%. The technology was then later adopted by the United States (US) space program (Haque, 2016). The fundamental impetus behind the development of solar PV harvesting technology was to mitigate the energy crises throughout the 1970s. Therefore, there has been a constant development of solar energy-harnessing technology since that time. Currently, solar PV technology has experienced a significant increase in importance as a leading renewable energy source. According to the International Energy Agency

(IEA), solar PV is expected to exceed coal and become the dominant renewable energy capacity by 2027, as illustrated in Figure 1.1.

However, the concerning issue of renewable energy is the power availability due to natural climate variability and climate change, which is beyond human control. For example, the production of electricity from solar energy heavily relies on the quantity of solar radiation and the duration of sunshine hours. Consequently, this reliance introduces unpredictability in power generation, which in turn impacts the decision-making processes involved in the day-to-day operations and long-term strategic planning within this industry. Hence, acquiring meteorological data is crucial in order to facilitate informed decision-making within the renewable energy industry (WMO, 2011). The primary motivating factor behind the development of the POWER project by NASA is the need for data. This project aims to promote research in three specific areas within the community: renewable energy development, building energy efficiency and sustainability, and agroclimatology applications (POWER, 2021). The NASA POWER product has been used in various applications worldwide, such as the study of solar energy (Awan et al., 2022; Chaichan et al., 2022; Kassem & Abdalla, 2022; Kumar et al., 2022), the selection of solar farm sites (Lurwan et al., 2017; Sabo et al., 2016), the assessment of pollution (Ganesh, 2023; Jat et al., 2021), agricultural practices (Gasol et al., 2023; Gupta et al., 2023; Torsoni et al., 2023), and the investigation of climate extremes (Chaudhary & Pandey, 2022; Kheyruri et al., 2023; Rockett et al., 2023).

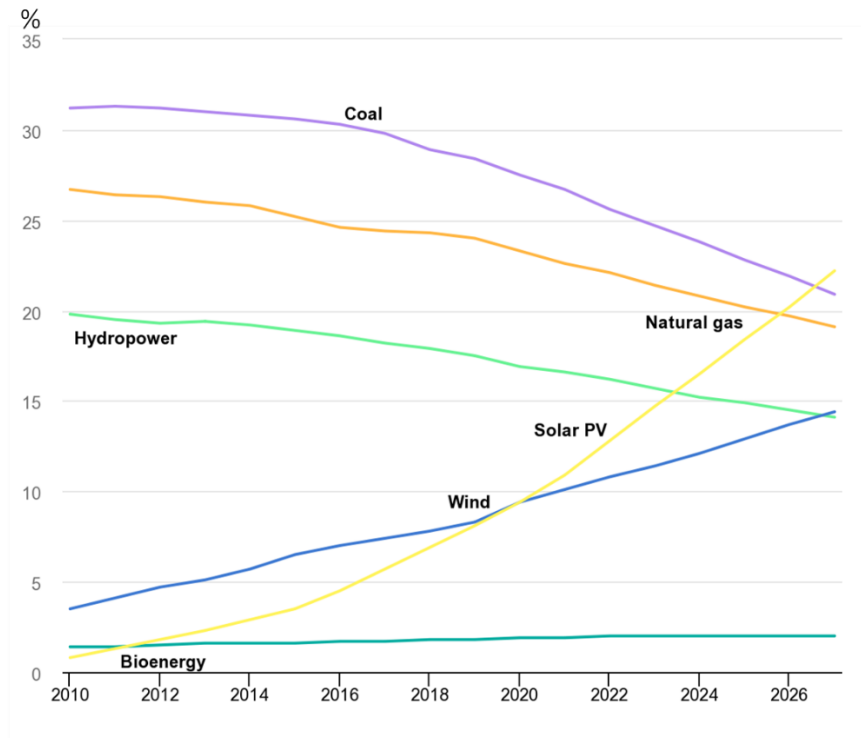


Figure 1.1 Share of total power capacity by different sources of energy 2010 – 2027 (IEA, 2020)

One of the essential initial decisions in harnessing solar energy is choosing a suitable location for solar farm establishment. The decision on the location should be approached strategically, as the solar farm's effectiveness depends on the location's suitability (Mokarram et al., 2020). The suitability of a location for solar farm establishment is defined based on several criteria and restrictions, adding complexity to the site selection task. Hence, this task requires an approach capable of incorporating many criteria; an approach most commonly used by researchers worldwide is the multi-criteria evaluation (MCE) (Eastman, 1999). Leveraging on the spatial analysis capabilities of the Geographic Information System (GIS), the integration of MCE and GIS, the GIS-based MCE has resulted in a robust and sound site selection approach, which has been demonstrated in several studies conducted globally (Akhtar et al., 2020;

Akkas et al., 2017; Al Garni & Awasthi, 2017; Asadi & Pourhossein, 2019; Barzehkar et al., 2021; Deveci et al., 2021; Habib et al., 2020; Khazael & Al-Bakri, 2021; Nguyen et al., 2021; Noorollahi et al., 2022).

The energy resources utilized in Peninsular Malaysia consist of coal (59.1%), natural gas (34.2%), hydro (5.5%), solar (0.9%), and others (0.3%) (refer to Figure 1.2) (EC, 2020). The Malaysian government's dedication to decreasing reliance on fossil fuels is shown in the National Renewable Energy Policy of 2010. The main goal of the policy is to attain a 20% proportion of renewable energy (RE) capacity within the overall energy composition of the country by the year 2050 (SEDA, 2011). The Twelfth Malaysia Plan (2021 – 2025) provides additional backing for the strategy since it sets a goal of increasing the country's RE generation to 31% of the whole installed capacity by 2025 (EPU, 2021). In addition, the adoption of the Feed-in Tariff (FiT) program, which enables the sale of electricity generated from renewable sources to Distribution Licensees (Tenaga Nasional Berhad (TNB), Sabah Electrical Sdn. Bhd. (SESB), NUR Power Sdn. Bhd.), exemplified the nation's commitment to investigate and utilize RE as a component of its domestic energy portfolio (Petinrin & Shaaban, 2015). The Energy Commission (EC) of Malaysia has initiated a competitive bidding procedure for Large Scale Solar (LSS) as part of its endeavors to attain the aforementioned objective. This initiative aims to reduce the Levelized Cost of Energy (LCOE) associated with implementing LSS (Abdullah et al., 2019).

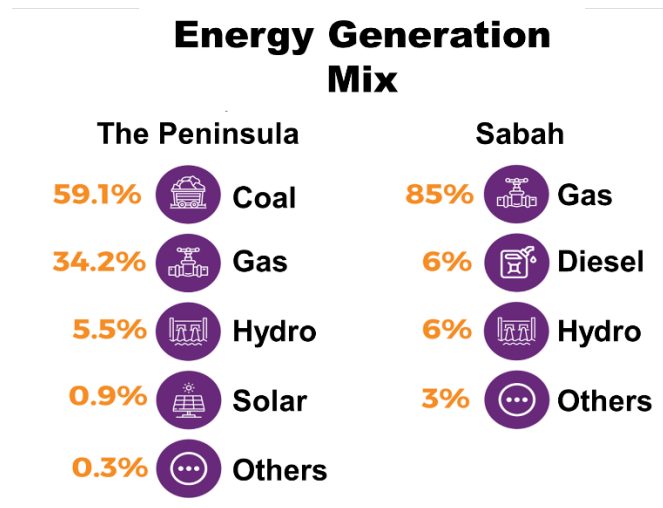


Figure 1.2 The energy mix for Peninsular Malaysia and Sabah (EC, 2020)

The Malaysian government's dedication to carbon emission reduction is evident in its efforts to attract over RM20 billion in investments for the electric vehicle (EV) industry (MIDA, 2023). Malaysia aims to position itself as a key player in EV manufacturing and production in Southeast Asia. However, the environmental benefits of EV technology, particularly in reducing carbon emissions, hinge on the source of electricity used for charging. It is essential that the energy for EV charging is not derived from fossil fuels. Additionally, it is noteworthy that the price of fossil fuels is prone to volatility, influenced by geopolitical events and economic factors. This volatility can exert upward pressure on global electricity prices, constituting a significant portion (90%) of the overall increase in the average electricity generation costs worldwide (Muta & Erdogan, 2023). In terms of the return on investment (ROI) for solar energy, based on a case study in Malaysia, the ROI in 25 years for a single-story house is approximately 91.53%, for commercial buildings, 203.65% and for educational institutions is about 107.10% (Wei & Saad, 2020). Therefore, to ensure energy security, and, affordability, and contribute to climate change mitigation, Malaysia would be better served by investing in the harnessing of solar energy.

Malaysia exhibits significant potential for the utilization of solar energy owing to its geographical proximity to the equator. According to Mekhilef et al. (2012), the estimated solar radiation in Malaysia ranges from 400 to 600 MJ/m² each month. The maximum solar energy intensity is projected to reach 24.5 MJ/m²/day, occurring during the months of August and November. Conversely, the minimum solar energy intensity is anticipated to be 2.2 MJ/m²/day, observed in December (Ashnani et al., 2014). Malaysia exhibits a notable capacity for solar energy production due to its consistently warm and sunny climatic conditions throughout the year. The potential of Malaysia is demonstrated by its position as the third-highest producer of solar energy in Southeast Asia, with a capacity of 438 megawatt (MW) in 2018 (Ludin et al., 2021).

Nevertheless, it is important to note that solar radiation exhibits geographical variations across different locations, leading to inconsistencies and fluctuations that can impact the feasibility of solar energy utilization (Al Garni & Awasthi, 2018). The lack of proper identification of an appropriate site for a solar farm has the potential to compromise both its cost-effectiveness and performance. This is exemplified by the situation of the Normandy Solar Road project in France. After only two years of operating, the French government announced its closure due to its failure to generate enough energy because of too many leaves falling on the solar panel (Moynihan & Montes, 2019). An additional illustration can be found in the case of the Medicine Hat solar facility located in Canada. This particular power plant, which had an initial investment of \$12 million, was decommissioned after five years. The reason for its closure was mostly attributed to its limited electricity generation capacity of just one MW during optimal summer conditions. This outcome was largely influenced by the fact that the country experiences relatively low levels of solar radiation (Hunt, 2019).

Consequently, the initial stage in guaranteeing a financially viable and efficient solar farm is the identification of an appropriate location prior to its installation.

Venturing into solar energy harnessing is not something new for the study area, George Town Conurbation, since there are various efforts taken by both government and private sector in pushing to harness solar energy. The Seberang Perai City municipality (MBSP), a municipality within the study region, has demonstrated pioneering efforts by entering into a Supply Agreement of Renewable Energy (SARE) with TNB, a prominent Malaysian multinational energy provider, for the implementation of a solar power program (Nambiar, 2019). The SARE program is an agreement involving: TNB, TNB's customer, and registered solar PV investors (RPVIs). It includes the obligations associated with the solar PV system, solar energy meter, and billing collection among these parties (Abu Samad, 2020). The government sector has undertaken another initiative, namely the execution of a solar Power Purchase Agreement (PPA) between Universiti Sains Malaysia (USM) and a Malaysian clean energy solutions company. This agreement aims to establish a 10.6 MW on-site rooftop solar system within the university campus. The campus aims to meet 75% of its peak electricity demand and 40% of its overall electricity consumption, resulting in a potential reduction of 30% in utility expenses and eliminating 217,705 metric tonnes of carbon emissions (USM, 2021). One of the several private endeavors pertaining to solar energy inside the research region involves the implementation of solar panels by Intel Malaysia on the company's facilities in Kulim and Penang. According to Chikkodi (2021), the solar farm constructed by Intel outside of the United States of America (USA) is the company's largest project of its kind. This solar farm is responsible for generating 15% of Intel's global on-site solar PV electric power capacity. It is predicted

that this initiative will result in a reduction of approximately 3,800 tonnes of carbon emissions.

1.2 Problem Statement

As stated in the preceding section, acquiring a meteorological dataset is necessary for strategic planning and daily operations to facilitate well-informed decision-making within the solar energy industry. However, meteorological data is usually expensive, time-consuming and challenging to collect especially in remote locations (Thomas et al., 2019). Furthermore, in developing countries, specifically Malaysia, only a few meteorological stations collect solar variables compared to other parameters, such as rainfall. The rainfall data was measured by two government departments, the Department of Irrigation and Drainage (DID) and the Malaysia Meteorological Department (MMD), hence, contributing to a dense coverage of rainfall data in Malaysia. However, this is different for solar radiation, as it is only measured in a selected few meteorological station by MMD. This is reflected in the existing literatures in Malaysia using observed rainfall data (Hanif et al., 2022; Khan et al., 2019; Muhammad et al., 2020), while for solar radiation parameters, satellite estimates or individual data collection are used (Lurwan et al., 2017; Sabo et al., 2016).

Therefore, satellite estimates of meteorological data are better alternatives for addressing observed data limitations, and one of them is the data provided by the NASA POWER project. The NASA POWER data is freely available for users to download and utilize in any model. The datasets obtained from NASA POWER are created by using numerical weather prediction models, which are simulated based on a collection of meteorological observations. Compared to other weather simulation products, the NASA POWER's strength lies on its user-friendliness and the flexibility offered to the

user to download single-point or gridded data in the case of regional and global downloads (Rodrigues & Braga, 2021b). The primary issue associated with employing satellite-derived estimates is the level of precision in predicting localized meteorological conditions. The quality of the GIS-based MCE model is contingent upon the accuracy of the data. Therefore, if the NASA POWER data is demonstrated to be precise in estimating the meteorological conditions in the George Town Conurbation region, it would enable end-users to access near-real-time sound weather data in the study area or make estimations at a local scale.

Although in Southeast Asia region, the NASA POWER data has been applied to many different studies, such as in agriculture (Silva et al., 2022; Suciantini et al., 2023; Yuan et al., 2022), forest fire (Kanga et al., 2017), renewable energy (Lurwan et al., 2017; Sukarso & Kim, 2020; Syahputra & Soesanti, 2020; Winardi et al., 2022). However, it is noteworthy that these studies have not incorporated an assessment of the accuracy of the NASA POWER data. Previous research conducted in the area has utilized NASA POWER data in conjunction with accuracy evaluation. These investigations have encompassed several fields, such as hydrology (Ngurah et al., 2022; Yasidi et al., 2023), renewable energy (Harsarapama et al., 2020), and climatology (Tan et al., 2023). Consequently, there has been a lack of emphasis on doing accurate assessments of NASA POWER data inside the region, particularly in Malaysia. It showcases a knowledge gap in the performance of NASA POWER data in estimating the local tropical Malaysian climate conditions.

The task of identifying an appropriate site for solar farms is a multifaceted issue that involves the consideration of several decision criteria that determine the viability of a location for the purpose of capturing solar energy. This assessment also entails the evaluation of constraining variables assessed (Al Garni & Awasthi, 2018). The

evaluation of these criteria and limiting factors is predicated on their potential effects, whether positive or negative, on the efficiency and financial implications of the energy generation process. Furthermore, the identification of potential sites holds significant strategic importance in terms of predicting annual power output and assessing financial feasibility (Sengupta et al., 2015). The locations play a critical factor in determining the cost of solar energy harnessing, in which the upfront cost for installing a solar farm or solar panels is usually higher than the conventional energy sources but with lower operating costs and shorter payback period (IRENA, 2023a). In a study conducted by Wei and Saad (2020), the payback period for installing 61.1 kWp and 224.3 kWp for commercial buildings and educational institutions is approximately 8.2 years and 12.2 years, respectively. The impact of solar radiation duration on the payback period is highlighted, further emphasizing the significance of strategic solar farm siting.

The utilization of GIS is prevalent in site selection studies due to its ability to integrate diverse datasets to achieve certain goals. Hence, integrating GIS data with diverse factors that impact site selection might serve as inputs for conducting MCE (Ali et al., 2019). Moreover, the utilization of the AHP within MCE has the potential to amalgamate the perspectives of knowledgeable individuals and decision-makers through a systematic assessment of various elements, hence enabling the attainment of particular objectives within a GIS framework (Höfer et al., 2016).

The MCE methodology has been empirically demonstrated as an effective approach for addressing intricate challenges, particularly those involving several criteria that impact a singular purpose (Anwarzai & Nagasaka, 2017). Several prior studies have successfully showcased the effective utilization of GIS-MCE in the assessment of suitability for solar energy applications (Ali et al., 2019; Anwarzai & Nagasaka, 2017; Doorga et al., 2019; Finn & McKenzie, 2020; Ruiz et al., 2020;

Teixeira et al., 2018). However, most studies conducted for solar energy applications do not incorporate thorough model's evaluation. Hence, this study attempts to bridge the gap between applying GIS-MCE in site selection for solar energy and model evaluation. It is important to highlight that the utilization of GIS-MCE in Malaysia is limited, particularly within the domain of RE. The investigation carried out by Lurwan et al. (2017) only concentrates on determining the most suitable site for the development of PV in Selangor, Malaysia. Conversely, the research conducted by Durrany Zulkifly and Mohd Said (2022) focuses on Melaka, Malaysia. The absence of a comparable study undertaken in the George Town Conurbation zone highlights a gap in knowledge regarding the precise criteria utilized in the GIS-MCE approach to determine potential locations for solar farms in this area.

1.3 Research Questions

Based on the preceding analysis of the problem description, two distinct research questions can be derived:

1. What is the level of precision exhibited by the NASA POWER data in accurately depicting solar and other climate factors within the Georgetown Conurbation region?
2. Where are the optimal locations for developing solar farms inside the Georgetown Conurbation region?

1.4 Research Objectives

The primary objective of this study is to determine the most suitable locations for solar farms inside the Georgetown Conurbation. This will be achieved by integrating NASA POWER data with the GIS-based fuzzy MCE model. The research purpose for this study is outlined in detail as follows:

1. To evaluate the performance of NASA POWER in estimating maximum temperature, minimum temperature, mean temperature, relative humidity, solar radiation, wind speed mean and rainfall in Georgetown Conurbation from 1985 to 2021.
2. To identify suitable sites for solar farm establishment in Georgetown Conurbation generated by GIS-based fuzzy MCE model with NASA POWER and observed meteorological data.

1.5 Scope of the study

The study focused on solar PV panels, which can either be ground mounted or roof panels due to the limitation of land availability in the study area. The analysis done in this study will prioritize but not be limited to the location suitable for LSS as it offers a great return on investment compared to the roof panels (Aly et al., 2017). This study would not consider other solar panels for several reasons, such as technology, application limitations, and cost.

The research chooses the study area of the George Town Conurbation region in the northern part of Peninsular Malaysia. This location was chosen for three main reasons: the area has the highest population among the other areas in the northern part of Peninsular Malaysia (DOSM, 2022a), hence the highest electricity demand due to its rapid urbanization owing to its intense industrial activities (Samat & Mahamud, 2019), and finally because of data availability. Therefore, the study will only evaluate the suitability index of the area within the George Town Conurbation region.

NASA POWER meteorological data were used in this study for several reasons; the project is tailored explicitly for photovoltaic and renewable energy industries (Sayago et al., 2020). The second reason is that the NASA POWER project provides

near real-time data for a resolution of 50km latitude-longitude simulated by weather prediction models using a set of meteorological observations as a basis (Monteiro et al., 2018). The final reason is its usability; the NASA POWER website allows users to download data in three different forms: single point, regional endpoint, and global endpoint for the entire globe (Rodrigues & Braga, 2021a).

In achieving the objectives of this study, the GIS-Based Fuzzy MCE (AHP) technique is used. The technique facilitates site selection tasks while adapting to the users' specific needs by integrating the tasks' quantitative and qualitative criteria (Zambrano-Asanza et al., 2021). Although this technique has been criticized in several literatures for its rank reversal (i.e., changes of parameters influence all other parameters) (Elliott, 2010; Yousefi et al., 2018), a consistency test is employed in this technique to overcome the inaccuracy through inconsistent judgment screening (Saaty, 1990). Therefore, this technique has been chosen due to its capability as a decision-support tool and its robustness and flexibility in solving complex decisions, acknowledged by the international scientific community (Al Garni & Awasthi, 2018).

1.6 Significance of the study

1.6.1 Theoretical Aspect

One of the significances of this study is the accuracy assessment of NASA POWER data in estimating a local scale climate condition. The product of satellite estimates is essential for sustainable renewable energy development planning, especially for areas with sparse meteorological stations. However, satellite estimates are often biased, particularly the local scale estimates of NASA POWER data, due to their coarse resolution (latitude 0.5° x longitude 0.5°) (Mo et al., 2020). Therefore, if the performance of NASA POWER data in estimating local scale climate conditions

can be proven satisfactory, it will benefit the other end users, especially those located within sparse meteorological stations and remote areas. The results from the NASA POWER data accuracy assessment increase its application value for future sustainable renewable energy development planning at a local scale.

Furthermore, this study adds to the existing body of knowledge by providing additional criteria that may be used to assess the appropriateness of a site for the development of a solar farm. The selection of the initial set of criteria is determined through a comprehensive assessment of existing literature. Subsequently, local experts' comments are sought to finalize the criteria, taking into account the specificities of the local climate and geographical factors. The additional measures undertaken in finalizing the criteria are necessitated by the fact that the appropriateness requirements for installing solar farms are contingent upon the unique characteristics of each site. Furthermore, it should be noted that no comparable investigation has been carried out within the same research region or in proximity. Therefore, other end-users can use this study's criteria for future solar energy development planning.

Another significant contribution of this study is related to the GIS-based Fuzzy MCE's output validation procedure. Most existing studies that use this model are lacking in the validation procedure to confirm the quality and accuracy of their final suitability map. Some studies will either use qualitative and quantitative validation to assess their suitability map's accuracy or sensitivity analysis to assess the stability of the model developed. However, this study will use both methods to ensure a comprehensive model evaluation. Using both validation methods increase users' confidence in the model's reliability and reduces the risk of wrong decision-making.

1.6.2 Practical Aspect

Countries around the globe, including Malaysia, are ramping up their effort in clean energy transition as the Conference of Parties 2021, or COP26, held in Glasgow, has emphasized the need to scale up the deployment of clean power generation to achieve the Paris Agreement's goal in maintaining the global temperature increase below 1.5°C by 2030 (UN, 2022). The findings of this study may foster Malaysia's clean energy transition by providing essential information on suitable locations for solar farm establishment in the George Town Conurbation region while ensuring an optimized centralized grid network and resource allocation. As the final suitability map is produced through a structured and scientific approach, the map can be used by the local's state government to justify and convince potential investors to invest in solar energy for the study area. One of the vital aspects of the clean energy transition is clean energy access for all. Hence, the outcome of this study may support the Ministry of Natural Resources, Environment and Climate Change (NRECC) in developing just energy transition policy and planning for the electricity grid network that leaves no one behind.

1.7 Thesis organization

The structure of this thesis is as follows: it begins with an introduction to the research topic, followed by a comprehensive review of the relevant literature. The subsequent sections outline the research techniques employed and provide an overview of the subject area. The findings are then presented and analyzed in the results and discussion section. Lastly, the thesis concludes with a summary of the main points and offers recommendations for future research. The following is a comprehensive breakdown of the content covered in each chapter:

Chapter One of this thesis discusses the background of the study, highlighting that the primary motivation for venturing into RE is to mitigate climate change. This chapter also briefly discusses the current efforts made by the Malaysian government to increase the proportion of RE in the national energy mix. This chapter highlights the problem statement of this study, which is that without proper and strategic planning, there will be drawbacks in solar energy harnessing. The study's objectives are also presented, and the final section of this chapter defines the scope and significance of this study.

Chapter Two of this thesis reviews the existing literature on renewable energy, focusing more on solar energy and GIS-based site selection for solar farms. The first section provides a general overview of renewable energy, solar energy and its theory. The following section provides information on solar farms and solar farm mapping. This was followed by the introduction of NASA POWER data and its performance based on the evaluation made by existing studies. Next is the discussion on the global application of GIS in site selection problems for solar farms, focusing on different types of MCE approaches and the general criteria used to define the suitability of a location. The model evaluation approaches are discussed in the following section, then the conceptual framework of this study. The chapter ends with a short conclusion justifying the method chosen for this study.

Chapter Three of this thesis describes the study area, the George Town Conurbation region. This chapter provides geographic and general information about the area, including its location, climate, and land use. This chapter also discusses the reasons for selecting this area for the study. Finally, the data description and full details of the research methodology are presented.

Chapter Four of this thesis presents the investigation findings, which are analyzed and discussed afterwards. This chapter presents an analysis of the performance of NASA POWER data, along with the presentation of the final suitability map. This chapter provides a comprehensive analysis of the key factors considered, in addition to the original criterion, while selecting the ultimate prospective site for solar farm development.

Chapter Five serves as the concluding section of this research endeavor, whereby the primary author presents their final thoughts and recommendations for future study endeavors. This chapter provides a concise overview of the findings derived from the study and offers suggestions for enhancing future research endeavors.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Chapter 2 provides an overview of the completed literature review on the topic issue. The initial section provides a contextual framework for understanding RE requirements and the various sources it encompasses. Followed by the general information and theory on solar energy harnessing, including its positive and negative impacts on the environment and society. The following section presents the work on solar farm mapping at the international and national levels. The review of NASA POWER data assessment conducted in previous studies is provided in the following section. Subsequently, the present chapter delves into utilizing GIS in the context of site selection endeavors for solar farms. Specifically, it examines various methodologies known as MCE techniques and the overarching factors commonly employed in prior research to establish the appropriateness of a given site. The model evaluation approaches are discussed in the following section, then the conceptual framework of this study. The chapter concludes with a summary that provides a rationale for the selected research methodology employed in this study.

2.2 Renewable Energy

The global population is experiencing the consequences of climate change in real time. According to the special report by the IPCC, the global economies' dependencies on fossil-fuel-based materials and high resource consumption lifestyles are the major contributors to GHG, which is responsible for global warming and climate change (IPCC, 2018). As mentioned in Chapter 1, United Nations member states are taking responsibility for addressing climate change through an agreement made under

the Paris Agreement (UN, 2015). In this agreement, Parties pledge to reduce carbon emissions as one of the concrete steps in maintaining the global temperature rise well below 1.5°C.

The energy sector is recognized and acknowledged as the primary cause of climate change because the sector emits 86% of the total global GHG (Friedlingstein et al., 2020). Therefore, the focus for climate change solutions revolves around the energy system, where the transition to clean energy production is the primary way to limit climate change (Clarke & Wei, 2020). The 2021 Conference of Parties, also referred to as COP 26, which took place in Glasgow, emphasized the imperative for participating nations to enhance the implementation of renewable energy generation and increase their endeavors to expedite the reduction of coal powerplant operations (UN, 2022).

Renewable energy is produced by exploiting replenishable natural resources without exhausting the earth's resources. According to the research conducted by Wang et al. (2023), nuclear power and renewable energy exhibit a positive relationship with economic growth while emitting low-carbon emissions. As of 2022, 39.7% of the sources for global power generation are from renewable energy, including nuclear energy sources (see Figure 2.1), in which the target for the 1.5°C pathway should be increased to 91% by 2050 (IRENA, 2023b).

Among the renewable energy sources, the most mature and commercially developed is hydropower, which explains why it has had the largest percentage of electricity generation since 2008 (Shafiqur Rehman et al., 2015). Following that are the nuclear energy sources, whose percentages in electricity generation are declining with time. According to the research conducted by Bohdanowicz et al. (2023), the decrease in nuclear energy usage can be attributed to the unfavorable perceptions held by the European Union (EU) populace. This negative sentiment arises from the perceived

hazards of nuclear energy, including the potential for system failures and the release of radioactive materials. Between 2008 and 2022, there is an increasing trend in electricity production via wind, solar, and bioenergy. The main drivers of the increasing trend include government policies and incentives (Colasante et al., 2022) and positive perceptions and social behavior toward these types of renewable energy sources (Schulte et al., 2022).

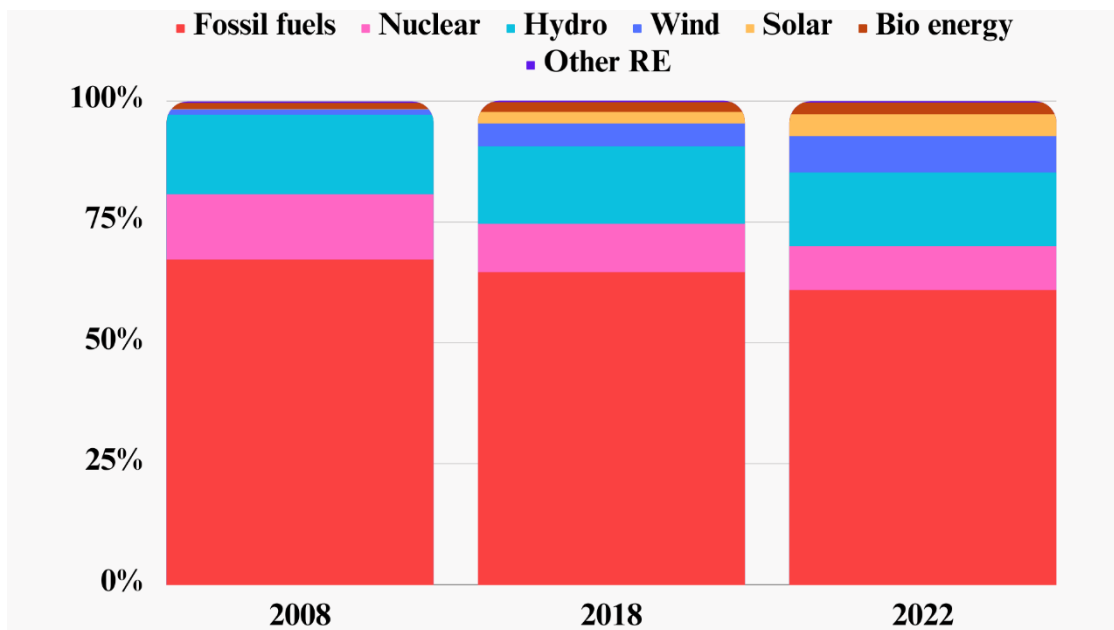


Figure 2.1 Sources for global electricity generation mix (Ritchie et al., 2022)

Although it can be seen in Figure 2.1 that wind energy exhibits an increasing trend, this thesis focuses on solar energy, as according to Figure 1.2, the absence of wind energy sources indicates the potential of wind energy harnessing in Malaysia is very low. The World Energy Outlook 2020 characterizes solar energy as "the emerging dominant force in the electricity sector," highlighting its potential to drive economic growth (IEA, 2020). Furthermore, solar energy as an energy source is globally accepted by the public in various sectors, promoting the deployment of the technology in a wide range of sectors. For instance, the industrial sector (Ismail et al., 2022), residential

sector (Schulte et al., 2022), building sector (Chandel et al., 2022), and agriculture sector (Pascaris et al., 2022).

2.3 Solar Energy

Solar energy is obtained from the sun, with the Earth's surface exposed to substantial solar radiation. This radiation can be harnessed and transformed into electrical energy by using solar (Hao et al., 2022). Solar energy is often regarded as a sustainable and environmentally friendly form of energy with significant potential to address the escalating need for electricity in numerous nations (Doljak & Stanojević, 2017).

2.3.1 Theoretical background of solar energy

Solar energy is commonly quantified using Global Horizontal Irradiance (GHI) or solar radiation. The GHI refers to the cumulative shortwave radiation received by the Earth's surface in a horizontal plane (Hassaan et al., 2021). GHI utilizes Concentrating Solar Power (CSP) or PV technology to create electricity. CSP and PV systems capture GHI and transform it into electrical energy (Alami Merrouni et al., 2018). The estimation for the year 2018 revealed that solar PV electricity generation capacity constituted approximately 34% of the overall newly installed power generation capacity on a global scale. This finding serves as evidence for the reliability and efficiency of PV technology (Jager-Waldau, 2018).

The efficiency of a solar energy generating system is typically influenced by many spatial variables. The electric power derived from solar PV systems exhibits a favourable correlation with the quantity of solar radiation and the sunshine duration (Al Garni & Awasthi, 2018). Regions characterized by lower average temperature, lower relative humidity, and higher sunshine duration are deemed more favourable for

establishing solar farms (Yelmen & Çakir, 2016). This conclusion is drawn from observations where the combination of high temperature and relative humidity led to a decline in electric power production. Moreover, the configuration of land topography, particularly slope and aspect, can impact the distribution of solar radiation throughout the Earth's surface. This can result in localized shadow effects, thereby influencing the capacity for energy generation (Pietras-Szewczyk, 2017). Furthermore, the factors that contribute to cost-effectiveness and low operational costs include accessibility, the reduction of construction expenses, the mitigation of electricity loss during transmission, and the avoidance of costs related to the extension of new transmission lines (Hassaan et al., 2021). The utilization of GIS in the planning and establishment of solar PV farms is underscored by the notable influence of geographical determinants on the efficiency of these systems. This highlights the exceptional capabilities of GIS in capturing, managing, modeling, analyzing, and visualizing spatial data (Resch et al., 2014).

2.4 Solar Farm

In the pathway of reducing carbon emissions via solar energy harnessing while protecting the nation's energy security, solar farms are considered a “nationally significant” infrastructure (Roddis et al., 2020). The terms solar park, solar fields and solar farms are interchangeable as these refer to arrays of ground-mounted solar PV panels that convert sun radiation into electricity. Solar farms are classified based on their scale, ranging from small-scale solar farms that consist of small arrays of solar PV panels, producing less than 1 MW of electricity, to mega-scale solar farms that cover thousands of hectares and produce 2000 MW of electricity (Wolfe, 2019).

2.5 Solar Farm Mapping

Although solar energy is classified as green energy due to its zero-carbon emission, there are still adverse impacts on the environment and biodiversity from a solar farm (Pratiwi & Juerges, 2020). For instance, degradation of soil quality, erosion and water pollution during the land clearing phase, air pollution during the construction phase, increased water consumption during operations, and the disruption of natural wildlife habitat, risking the local biodiversity (Darwish et al., 2018). These impacts are considered as spatial-related impacts of a solar farm. Hence, solar farm mapping is required to address and identify potential adverse impacts to its' surroundings (Hou et al., 2020). The solar farms' map also complements the conventional solar generating capacity inventories (Byers, 2018; IEA, 2020; IRENA, 2019).

2.5.1 International level

As mentioned in the previous section, a solar farm map that shows the exact location of solar farms can answer spatially related questions that arise in solar farm development. For instance, how much capacity has been built, where are the facilities concentrated, and how have the facilities impacted the surrounding biodiversity. Figure 2.2 shows the global solar farm mapping generated by Kruitwagen et al. (2021), which uses a longitudinal corpus of remote sensing imagery, machine learning and extensive cloud computation infrastructure. The results indicate that most of solar farms are situated on agricultural land, with cropland being the most common location, followed by arid lands and grasslands. The most extensive solar farms are in China, India, and Mexico, specifically in semi-arid and desert regions (Wolfe, 2019). However, most of the development in Europe is concentrated in densely populated areas, occupying agricultural and brownfield land (Roddie et al., 2020).