International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

March 2024	Issue 58	Volume 16	Number 1	Pages 218-226

ESTIMATION OF SOLAR POTENTIAL AND URBAN LAND USE CLASSIFICATION USING SATELLITE IMAGERY AND DIGITAL SURFACE MODELS

A. Chompoosri [1]   S. Sangpradid [2]   W. Chokkuea [1]   T. Laosuwan [1]

1. Department of Physics, Faculty of Science, Mahasarakham University, Kantarawichai District, Maha Sarakham, Thailand, 64010258003@msu.ac.th, wutthisat.c@msu.ac.th, teerawong@msu.ac.th
2. Department of Geoinformatics, Faculty of Informatics, Mahasarakham University, Kantarawichai District, Maha Sarakham, Thailand, satith.s@msu.ac.th

Abstract- This study aims to estimate the solar potential of a given area by integrating urban land-use data from Sentinel-1 imagery and digital surface models (DSM) using the Solar Radiation tool. Solar irradiation exhibits temporal variations influenced by climatic conditions and the location of the sun. Accurate prediction of solar radiation is crucial for decision-making in renewable energy and urban planning. The Random Forest algorithm is employed for urban land use classification, providing reliable results in distinguishing different land use categories, especially urban areas. Evaluation metrics such as branching factor, miss factor, urban detection percentage, and quality percentage assess the performance of the classification model. The estimation of solar potential maps allows for the identification of areas with high solar energy potential, facilitating site selection for solar energy installations. The study highlights the challenges of calibrating atmospheric parameters and emphasizes the importance of considering key inputs such as atmospheric transmission, elevation, slope, and orientation in the Solar Radiation tool for accurate calculations. The findings contribute to understanding solar potential mapping, remote sensing applications in urban land use analysis, and inform decision-making for sustainable development and renewable energy utilization.

Keywords: Remote Sensing, Digital Surface Models (DSM), Random Forest Algorithm, Solar Radiation Tool, Renewable Energy Utilization.

1. INTRODUCTION

The global demand for electricity continues to rise, leading to an increasing shift towards exploring alternative energy sources. The use of fossil fuels as the primary source of electricity has contributed significantly to environmental pollution, climate change, and global warming. In response, governments and private organizations worldwide are investing heavily in renewable energy to meet their energy needs while reducing their carbon footprint. From the information of the International Energy Agency, global renewable energy capacity is projected to produce by 50% between 2019 and 2024, with solar photovoltaics leading the growth. Renewable energy sources are expected to account for nearly 30% of the world's electricity generation by 2024 [1]. Thailand is among the countries that recognize the importance of renewable energy and its potential to meet its growing demand for electricity while mitigating environmental damage. The Thai government has implemented several policies, including the Alternative Energy Development Plan (AEDP) and the Power Development Plan (PDP), to promote the use of renewable energy. The goal of these policies is to upsurge the share of renewable energy in the country's energy mix and reduce its dependence on fossil fuels.

In recent years, Thailand's renewable energy section has witnessed significant growth, with a total installed capacity of over 11,000 MW from solar power, wind power, biomass, and hydropower. The country has set an ambitious target to make 30% of its total electricity from renewable energy sources by 2037 [2]. Furthermore, the promotion of energy production from existing renewable energy sources, the progress of the potential of renewable energy production with appropriate technology, and the progress of renewable energy for the benefit of social and environmental dimensions for the community are also prioritized [2]. Solar energy is a solitary of the most abundant renewable energy sources in Thailand due to the country's geographical location, which receives high levels of solar irradiance throughout the year. According to the Thai government has implemented various policies and incentives to promote the adoption of solar energy, including net-metering programs and investment tax incentives for businesses and households that install solar panels. Furthermore, the AEDP has set a target to increase its solar power capacity to 6,000 MW by 2037, which would account for 15% of the country's total installed capacity [2].

To achieve this target, accurately assessing the potential of renewable energy sources is crucial. Remote sensing technology has revolutionized the way we view and understand the Earth's surface, and one of its

Registered: 230519   Article Info: 1724   Accepted: 240229
Reserved: 230728   Available: 240331

significant applications are in the field of land-use and land cover analysis. This involves the specifying and mapping of different types of land use, such as urban areas, forests, agriculture, and water bodies [3]. Remote sensing data can be used to monitor changes in land use and develop land use models that help predict future changes [4]. It has also proven useful in disaster management, such as drought monitoring [5-16]. With the increasing demand for renewable energy sources, remote sensing has become an essential tool in assessing the potential for renewable energy generation, particularly solar energy. By using remote sensing data, researchers can identify suitable locations for solar energy generation based on factors such as land use, topography, and solar radiation. Solar radiation is the primary source of solar energy, and it is affected by various factors such as topography, atmospheric conditions, and land use. Remote sensing is a technology that can provide spatially explicit data on these factors, which can be used for modelling the potential of solar energy in the urban area.

Urban areas are constantly expanding, and the demand for accurate and informed data on land-use and land-cover in urban areas is increasing. The rapid expansion of urban areas, driven by demographic, economic, social, and political factors, is a complex process that often leads to negative impacts on land-use and land-cover changes [17]. Remote sensing technology has become an essential tool for urban planners, policymakers, and researchers in mapping and monitoring land use in urban areas [18]. The Sentinel-1 satellite, through its Synthetic Aperture Radar (SAR) sensor, has shown great potential in mapping urban areas due to its ability to penetrate clouds and capture images regardless of weather conditions [19]. The use of SAR data has proven to be effective in urban area classification and mapping of topographies such as roads, buildings, and vegetation [20]. Several studies have been conducted on the use of remote sensing and SAR data for urban area classification based on spectral-based classification [21], object-based classification [22], and machine learning [23] techniques.

The potential for solar energy in urban areas has gained increasing attention due to the growing demand for renewable energy sources and the require to reduce carbon emissions. Solar energy is a promising source of renewable energy for urban areas due to its ability to generate electricity from rooftops and facades of buildings, reducing the need for large land areas for energy production. Solar energy solutions, particularly solar photovoltaic (PV) systems, offer significant potential for addressing energy scarcity and improving living standards. These systems, commonly installed on building rooftops, efficiently convert solar energy into electric power, benefiting from technological advancements that have reduced manufacturing and installation costs [24, 25].

Solar radiation is a crucial factor to consider when installing solar power plants, and it is important to identify areas with high solar radiation and predict its distribution over space and time. Solar radiation analysis can be conducted at specific points or across large areas, including administrative districts, and it involves spatial mapping as well as temporal analysis and visualization [26]. This paper proposes to evaluate the potential of solar energy in urban areas by utilizing remote sensing technology and analyzing solar radiation data. This involves employing remote sensing techniques, particularly using Sentinel satellite data with its SAR sensor, for accurate mapping and classification of urban land use. Secondly, the paper intends to approximate the solar radiation map in the urban area. Solar radiation plays a crucial part in assessing the potential for solar energy and informing planning processes. By analyzing the spatial and temporal distribution of solar radiation in urban areas, areas with high solar potential, such as rooftops and open spaces, can be identified. This information is valuable for decision-makers, urban planners, and stakeholders involved in promoting renewable energy and facilitating sustainable development in urban environments.

2. MATERIAL AND METHOD

2.1. Study Area

The study area for estimating the solar radiation map in the urban area is Kantharawichai district, located in Maha Sarakham province, Thailand. Kantharawichai district is situated within the geographic coordinates of 16.279577 N latitude and 103.243263 E longitude. Kantharawichai district is a predominantly rural area with some urban settlements. It is characterized by a mix of land use types, including residential areas, agricultural fields, commercial zones, and natural landscapes. The district experiences typical weather patterns and climatic conditions of the region, with hot and dry summers. The selection of Kantharawichai district as the study area is based on several factors. Firstly, Kantharawichai district is of interest owing to its potential for solar energy utilization. The district's geographical location and climatic conditions make it suitable for solar energy generation. By estimating the solar radiation map, we can identify areas with high solar potential, such as rooftops and open spaces, which can contribute to the evolution of solar energy projects and the encouragement of renewable energy in the district. Secondly, Kantharawichai district has a university located within its area, enabling the estimation of the solar power map. This estimation can effectively demonstrate the distinct differences between the rural and urban communities in terms of solar potential.

2.2. Satellite Data

In this study, we utilized the Sentinel-1 satellite data with its Synthetic Aperture Radar (SAR) sensor for accurate mapping and classification of urban land use in Kantharawichai district. The advantages of SAR technology, such as its all-weather imaging capability and high-resolution data acquisition, make it well-suited for urban land use analysis [27]. The Sentinel-1 satellite provided multi-temporal SAR data, enabling the capture of temporal changes in the urban landscape [28]. The SAR data were acquired for multiple time periods in the study area and underwent pre-processing steps, including radiometric calibration and speckle filtering, to enhance their quality and interpretability [29-30]. Image processing techniques and machine learning algorithms were then applied to the SAR images for feature extraction and classification of urban land use categories [31]. The classification results were validated using ground truth data obtained through field surveys or existing land use maps, and statistical metrics were employed to assess accuracy. By leveraging the Sentinel-1 SAR data and employing advanced image processing and classification techniques, this study aimed to achieve accurate mapping and classification of urban land use in Kantharawichai district. The outcomes of this research provide valuable insights into the spatial distribution and dynamics of different land use categories within the urban area. This information is essential for assessing solar energy potential and supporting sustainable urban planning and development.

2.3. Digital Surface Model (DSM)

The Digital Surface Model (DSM) plays a crucial role as the primary data in GIS technique for solar potential investigation. It represents a raster data containing height information, combining the ground height from a Digital Elevation Model (DEM) with the altitude of all objects on the surface, including trees, edifices, canopies, and other structures [32]. DSMs are commonly generated using photogrammetry techniques, which involve analyzing aerial or satellite imagery [33]. The DSM can be derived from various sources such as LiDAR (Light Detection and Ranging) images or ortho imagery, enabling the generation of detailed 3D models for a specific urban area. The utilization of DSMs in solar potential analysis is crucial for understanding the topography and physical features that influence solar energy availability. By considering the height information captured in DSMs, shading effects, obstructions, and other factors impacting solar radiation can be accurately evaluated. This information is vital for identifying suitable locations for solar energy installations, optimizing energy generation, and promoting sustainable urban development.

2.4. Methodology

The methods employed to estimate solar power potential from urban land use and digital surface model consist of several steps. Firstly, the preprocessing of Sentinel-1 data involves a series of seven processing steps. These steps include applying the orbit file to ensure accurate geolocation, removing thermal noise, eliminating border noise, radiometric calibration to standardize the backscatter values, applying speckle filtering to reduce noise and enhance data quality, performing range Doppler terrain correction to account for variations in terrain, and converting the data to decibel (dB) scale for better interpretation and analysis [30]. Secondly, the classification of urban land use is conducted using Random Forest methods. The pre-processed Sentinel-1 data is utilized along with ancillary data and contextual information to train a Random Forest classifier.

This supervised machine learning algorithm uses decision trees to classify different land use categories, enabling the identification and mapping of urban areas, vegetation, water bodies, and other land cover types. Finally, the estimation of solar power potential is performed by integrating the classified urban land use information with the digital surface model (DSM). Solar radiation modelling techniques are applied, taking into account factors such as shading, orientation, and slope, to estimate the amount of solar radiation received in different parts of the study area. This information helps identify areas with optimal solar conditions for potential solar energy generation.

2.5. Classification of Urban Land Use from Sentinel-1 using Random Forest Methods

The Random Forest method was employed to separate urban land use from Sentinel-1 data. This supervised machine learning process has proven effective in handling complex datasets and is widely used in remote sensing applications. The Random Forest algorithm is an ensemble learning technique that merges multiple decision trees to make forecast or categorization. Random Forest has been widely used in various domains due to its robustness and accuracy. Random Forests utilize an ensemble of tree forecasters, where each tree is built using a random vector of input variables sampled independently and with the same spreading for all trees [34]. The Random Forest approach leverages multiple decision trees to enhance prediction accuracy [35]. In the case of image classification, Random Forest constructs numerous decision trees, and each tree provides a class estimation. The final estimation is made based on the majority vote from all the trees in the Random Forest model [36]. The Random Forest categorization process for urban land use involves the following steps:

1) Data Preparation: Organize the input data with features (independent variables) and labels (dependent variable) to train the model,

2) Random Subsampling: Create random subsets of the data through bootstrapping, generating different training sets for each decision tree in the Random Forest,

3) Building Decision Trees: Construct decision trees using a subset of features and the corresponding bootstrap sample. Recursively split nodes based on a chosen criterion, such as the Gini index or information gain,

4) Independent Predictions: Make predictions or classifications independently with each decision tree in the Random Forest. For classification tasks, use majority voting; for regression tasks, use averaging,

5) Ensemble Aggregation: Combine predictions from all decision trees through aggregation. For classification, use majority voting to determine the final prediction; for regression, use averaging, and

6) Assessing Feature Importance: Evaluate the importance of features in the predictions to identify the most influential factors contributing to the classification results.

2.6. Evaluation of Urban Land-use Classification

Evaluation of the urban land-use classification by using the overlap between the urban area results and the urban reference map using the four statistical specifications including True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) [37]. The evaluation of area quality metrics in the context of urban land use classification typically includes the following metrics: branching factor, miss factor, urban discovery percentage, and quality percentage [38, 39].

2.7. Estimation of Solar Potential Map

In this study, the estimation of the solar potential map was conducted by integrating urban land use data from Sentinel-1 imagery and DSM using the Solar Radiation tool. Solar irradiation exhibits temporal variations throughout the day, month, and year, influenced by climatic conditions and the sun's position. The Solar Radiation tool utilizes the hemispherical viewshed algorithm, as described in [40-42], to calculate solar radiation for specific geographic areas or designated point locations. The tool requires inputs such as location, elevation, slope, orientation, and atmospheric transmission to accurately estimate solar potential. By calibrating all the necessary parameters, the estimation of solar potential for the entire city was achieved. The calculations were performed using the Solar Radiation tool, initially considering solar radiation across the entire DSM to account for shading effects caused by trees and other tall structures.

3. RESULT

Satellite image analysis using Sentinel-1 involves preliminary image processing before analyzing the Sentinel-1 satellite data to improve accuracy in detecting urban land us. This preprocessing step was crucial for adjusting the reflectance values of the Sentinel-1 satellite imagery by taking into account the interferometric coherence values for each polarization channel, namely VV and VH. Interferometric coherence values range from 0 to 1 and provide insights into the backscattering behavior of the different polarization channels. In the case of Sentinel-1 satellite images, the VV polarization typically exhibits higher backscattering values compared to the VH polarization. By considering the interferometric coherence values and analyzing the image, we observed high intensity values of sigma, indicating significant scattering behavior. These preprocessing steps were performed to ensure that the Sentinel-1 data were appropriately calibrated and ready for further analysis.

The results of the preprocessing stage for the Sentinel-1 data in the study area followed the established steps outlined for the preprocessing of Sentinel-1 data. These steps involved applying various techniques such as radiometric calibration, speckle filtering, and range Doppler terrain correction to ensure the data's quality and accuracy. The pre-processed Sentinel-1 data were then ready for subsequent analysis and estimation of solar potential in the study area.

3.1. The Results of Classification of Urban Land-use Random Forest Methods

In this research, the researchers employed a method called supervised classification with the Random Forest algorithm to classify urban or built-up areas. Supervised classification is a technique where the classification model is trained using labelled samples, and Random Forest is a popular machine learning algorithm that merges multiple decision trees for classification. To perform the categorization, sample areas were defined or selected as representative examples of built up and non-built-up areas. These sample areas serve as training data for the classification model. The results of the urban land-use classification revealed the distinct patterns and characteristics of urban land-use within the study area. The Random Forest algorithm successfully identified and differentiated between built up and non-built-up areas. The urban land-use map was shown in Figure 1.

The evaluation of the urban land-use classification results using the Random Forest algorithm is based on several area quality metrics, as shown in Table 1. These metrics provide insights into the accuracy and performance of the classification model. Here are the results for the specific metrics: Branching factor: The branching factor is calculated as 7.439. It represents the average number of classes assigned to each class. A higher branching factor suggests that there may be some overlap or confusion between classes, indicating a less distinct classification result.

Table 1. The evaluation results of urban land use classification

Quality metrics	Area level
Branching factor	7.439
Miss factor	0.289
Building detection percentage	87.582%
Quality percentage	61.458%

- Miss factor: The miss factor is calculated as 0.289. It represents the percentage of misclassified pixels or the proportion of pixels that were assigned to incorrect land use categories. A lower miss factor indicates a higher accuracy in classifying urban land use, with fewer misclassifications. Building detection percentage: The building detection percentage is calculated as 87.582%. It represents the proportion of correctly classified urban pixels (specifically buildings) compared to the overall number of urban pixels in the training area. A higher building detection percentage indicates a higher accuracy in identifying and labelling urban buildings.
- Quality percentage: The quality percentage is calculated as 61.458%. It measures the overall accuracy of the classification model, taking toward account both correct classifications and the exclusion of non-urban areas. It displays the percentage of correctly classified urban pixels relative to the total number of pixels identified as urban. A higher quality percentage indicates a more reliable classification result, with a lower inclusion of non-urban areas.

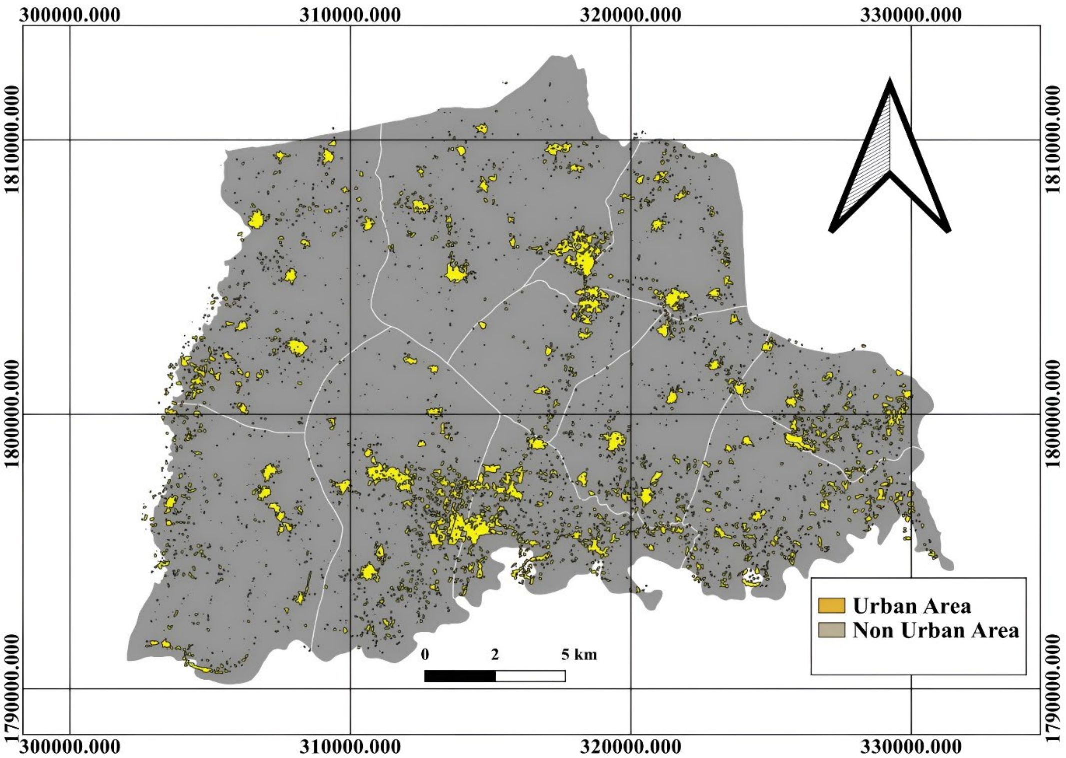

Figure 1. Built-up and non-built-up areas using Random Forest

These evaluation metrics provide valuable insights into the accuracy and performance of the Random Forest classification model for urban land use. They help assess the effectiveness of the model in distinguishing different land use categories and accurately identifying urban areas. These results are crucial for estimating the urban solar potential map in the next step, as they provide information on the quality and reliability of the classification output.

3.2. The Estimation of Solar Potential Map Results

The quantity of solar radiation collected at the Earth's surface is one a fraction of the total radiation that is incident on the outer atmosphere, which is determined by the properties of the atmosphere. It is indicated as the ratio of energy (average wavelength) reaching the Earth's surface, ranging from 0 (no transmission) to 1 (complete transmission). The energy collected at the Earth's surface is at its maximum along the shortest path via the atmosphere (directly above or overhead). Latitude is used to calculate the surface area (in decimal degrees, positive for the northern hemisphere and negative for the southern hemisphere) and is utilized in the computations due to variations in solar intensity caused by spatial differences. The solar potential within the study area is calculated in watts per square meter (Wh/m^2) since the intensity of sunlight varies based on location, necessitating the definition of specific zones within the study area.

The results provided in the table represent the estimated solar potential in different Tambon (sub-districts) for each month as shown in Table 2. Table 2 provides the estimated solar potential values for the entire tambon (subdistrict) area. These values represent the overall solar potential, considering all land uses within the tambon, including both urban or built-up areas and non-urban areas.

Upon analyzing the data, several observations can be made:

- Variation in Solar Potential: The solar potential varies across different Tambon and months. For example, in Tambon Na Sri Noan, the solar potential ranges from 8,763,474 Wh/m^2 in January to 10,064,959 Wh/m^2 in August. This indicates that the solar energy availability is influenced by both geographical location and seasonal changes.
- Seasonal Trends: There is a clear seasonal trend in the solar potential. Generally, the solar potential increases from January to a peak in either April or May and then gradually decreases towards the end of the year. This trend can be observed in most Tambon in the Table 3.
- Spatial Variation: The solar potential also varies spatially across different Tambon. For instance, Tambon Sri Suk consistently exhibits relatively higher solar potential values compared to other Tambon throughout the year. This suggests that Tambon Sri Suk may have favorable conditions for solar energy generation.

Table 3 show the results provided in the table represent the estimated solar potential specifically from urban areas or built-up areas in different Tambon (sub-districts) for each month. Table 3, on the other hand, specifically focuses on the estimated solar potential values from urban or built-up areas within the Tambon. These values highlight the solar energy potential within urbanized regions, where buildings, infrastructure, and other man-made structures are present. By isolating the solar potential from urban or built-up areas, we gain insights into the renewable energy potential within these developed zones.

Table 2. The estimated solar potential value in different Tambon (sub-districts) for each month

Month	Tambon (sub-districts)									
	Kok Pra	Kan Tha	Ma Ka	Tha Kon Yang	Na Sri Noan	Kham Reang	Kwao Yai	Sri Suk	Kud Sai Jo	Kham Tao
January	4,858,374	3,856,249	5,389,287	4,132,706	8,763,474	9,234,150	7,963,485	9,959,346	3,531,839	5,849,527
February	4,602,430	3,650,570	5,115,315	3,913,401	8,300,136	8,742,850	7,580,775	9,429,278	3,350,135	5,556,945
March	5,135,681	4,093,055	5,666,182	4,373,473	9,276,467	9,767,617	8,416,375	10,544,358	3,719,304	6,227,231
April	5,427,715	4,355,682	5,979,450	4,658,422	9,836,041	10,371,284	8,876,881	11,156,749	3,904,323	6,617,802
May	5,510,565	4,422,844	6,091,579	4,754,129	9,992,405	10,537,971	9,002,416	11,307,303	3,955,203	6,717,612
June	5,283,319	4,256,609	5,879,730	4,592,127	9,592,252	10,156,198	8,672,466	10,830,967	3,784,039	6,458,732
July	5,502,423	4,423,125	6,101,868	4,763,478	9,983,371	10,545,996	9,007,413	11,284,623	3,945,343	6,715,176
August	5,553,719	4,456,822	6,119,832	4,773,375	10,064,959	10,610,957	9,071,659	11,407,574	3,990,328	6,770,550
September	5,259,872	4,205,781	5,796,373	4,492,649	9,514,922	10,024,664	8,611,781	10,809,306	3,799,486	6,395,379
October	5,010,679	3,980,375	5,555,397	4,261,442	9,041,021	9,522,009	8,241,241	10,274,682	3,641,706	6,058,129
November	5,099,094	4,027,293	5,689,379	4,331,133	9,176,293	9,666,562	8,409,426	10,414,006	3,719,649	6,133,262
December	5,016,768	3,958,647	5,609,912	4,265,799	9,029,325	9,510,340	8,279,795	10,237,174	3,662,601	6,030,664

Table 3. The estimated solar potential value specifically from urban areas or built-up areas in different Tambon (sub-districts) for each month

Month	Tambon (sub-districts)									
	Kok Pra	Kan Tha	Ma Ka	Tha Kon Yang	Na Sri Noan	Kham Reang	Kwao Yai	Sri Suk	Kud Sai Jo	Kham Tao
January	523,616	241,115	563,326	873,714	608,628	841,793	504,434	480,592	452,130	480,850
February	445,030	208,425	484,631	751,832	524,733	723,676	433,417	416,937	386,325	414,271
March	481,962	231,363	536,135	832,950	578,112	795,955	473,631	463,537	423,027	455,792
April	487,583	240,483	557,777	871,337	596,047	821,299	482,659	481,739	33,850	467,710
May	480,570	240,626	566,028	877,985	597,159	822,644	482,461	483,478	435,459	464,490
June	383,475	190,628	422,346	719,770	462,473	645,686	347,318	369,935	335,630	353,229
July	401,146	199,096	438,701	748,714	482,804	672,897	361,870	386,660	350,000	369,805
August	414,115	203,812	441,250	758,765	493,559	686,527	369,641	396,817	356,651	381,861
September	407,183	196,082	422,164	724,394	476,263	662,187	361,096	382,907	346,532	373,310
October	404,327	188,927	411,113	697,004	463,175	644,103	359,090	370,821	341,055	367,572
November	419,523	192,165	422,569	711,408	473,055	660,082	371,394	377,189	353,197	377,379
December	412,842	188,474	415,163	699,463	463,541	647,894	363,658	369,064	347,649	369,619

Upon analyzing the data, several observations can be made:

- Variation in Solar Potential: The solar potential varies across different Tambon and months, focusing only on urban or built-up areas. For example, in Tambon Tha Kon yang, the solar potential ranges from 873,714 Wh/m^2 in January to 877,985 Wh/m^2 in May. This indicates that urban areas may have varied solar energy availability throughout the year.
- Seasonal Trends: Similar to the overall solar potential, there is a seasonal trend in the solar potential from urban areas. The solar potential tends to increase from January to a peak in either April or May and then gradually decreases towards the end of the year. This trend can be observed in most Tambon in the Table 3.
- Spatial Variation: The solar potential also varies spatially across different Tambon, focusing on urban areas. For instance, Tha Kon yang consistently exhibits relatively higher solar potential values compared to other Tambon throughout the year. This suggests that urban areas in Tambon Tha Kon yang may have favorable conditions for solar energy generation.

4. CONCLUSIONS

In conclusion, this study focused on estimating the solar potential of a given area by integrating urban land use data from Sentinel-1 imagery and DSM using the Solar Radiation tool. The results demonstrated the temporal differentiations in solar irradiation throughout the year and highlighted the influence of climatic conditions and the sun's location. The application of the Random Forest algorithm for urban land use classification proved to be effective, providing accurate and reliable results. The evaluation metrics, such as branching factor, miss factor, urban discovery percentage, and quality percentage, showcased the performance of the classification model and its ability to distinguish different land use categories, particularly urban areas.

The estimation of solar potential maps allowed for the identification of areas with high solar energy potential, which is crucial for decision-making processes related to renewable energy and urban planning. The integration of solar potential information can aid in the selection of suitable sites for solar energy installations, maximizing the utilization of solar resources and contributing to overall energy sustainability goals. The study also discussed the challenges in calibrating atmospheric parameters and the importance of considering atmospheric transmission, elevation, slope, and orientation as key inputs in the Solar Radiation tool for accurate solar radiation calculations. Overall, the findings of this study contribute to the understanding of solar potential mapping and the application of remote sensing technology and tools for urban land-use analysis. The results provide valuable insights for policymakers, urban planners, and stakeholders involved in promoting renewable energy and sustainable development, facilitating informed decision-making and effective utilization of solar resources.

ACKNOWLEDGEMENTS

This Research was Financially Supported by Mahasarakham University (Grant year 2021).

REFERENCES

[1] International Energy Agency, 2019, "Global Solar PV Market Set for Spectacular Growth over Next 5 Years", www.iea.org/news/global-solar-pv-market-set-for-spectacular-growth-over-next-5-years, 28 April 2023.
[2] Department of Alternative Energy Development and Efficiency, 2018, "Alternative Energy Development Plan (AEDP)", Ministry of Energy, Thailand.
[3] I. Aroonsri, S. Sangpradid, "Artificial Neural Networks for the Classification of Shrimp Farm from Satellite Imagery", Geographia Technica, Vol. 16, No. 2, pp. 149-159, 2021.
[4] S. Sangpradid, "Change Vector Analysis using Integrated Vegetation Indices for Land Cover Change Detection", International Journal of Geoinformatics, Vol. 14, No. 4, pp. 71-77, 2018.
[5] T. Laosuwan, S. Sangpradid, T. Gomasathit, T. Rotjanakusol, "Application of Remote Sensing Technology for Drought Monitoring in Mahasarakham Province, Thailand", International Journal of Geoinformatics, Vol. 12, No. 3, pp. 17-25, 2016.
[6] T. Rotjanakusol, T. Laosuwan. "Inundation Area Investigation Approach using Remote Sensing Technology on 2017 Flooding in Sakon Nakhon Province Thailand", Studia Universitatis Vasile Goldis Arad, Life Sciences Series, Vol. 28, No. 4, pp. 159-166, 2018.
[7] Y. Uttaruk, T. Laosuwan, "Drought Analysis Using Satellite-Based Data and Spectral Index in Upper Northeastern Thailand", Polish Journal of Environmental Studies, Vol. 28, No. 6, pp. 4447-4454, 2019.
[8] T. Rotjanakusol, T. Laosuwan, "Model of Relationships between Land Surface Temperature and Urban Built-Up Areas in Mueang Buriram District, Thailand", Polish Journal of Environmental Studies, Vol. 29, No. 5, pp. 3783-3790, 2020.
[9] N. Jomsrekrayom, P. Meena, T. Laosuwan, "Spatiotemporal Analysis of Vegetation Drought Variability in the Middle of the Northeast Region of Thailand using Terra/Modis Satellite Data", Technical Geography, Vol. 16, Special Issue, pp. 70-81, 2021.
[10] P. Meena, T. Laosuwan, "Spatiotemporal Variation Analysis of Atmospheric Carbon Dioxide Concentration using Remote Sensing Technology", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 48, Vol. 13, No. 3, pp. 7-13, September 2021.
[11] S. Sangpradid, Y. Uttaruk, T. Rotjanakusol, T. Laosuwan, "Forecasting Time Series Change the Average Enhanced Vegetation Index to Monitoring Drought Condition by using TERRA/MODIS Data", Agriculture and Forestry, Vol. 67, No. 4, pp. 115-129, 2021.
[12] T. Laosuwan, Y. Uttaruk, T. Rotjanakusol, "Analysis of Content and Distribution of Chlorophyll-a on the Sea Surface through Data from Aqua/MODIS Satellite", Polish Journal of Environmental Studies, Vol. 31, No. 5, pp. 4711-4719, 2022.
[13] Y. Uttaruk, T. Rotjanakusol, T. Laosuwan, "Burned Area Evaluation Method for Wildfires in Wildlife Sanctuaries Based on Data from Sentinel-2 Satellite", Polish Journal of Environmental Studies, Vol. 31, No. 6, pp. 5875-5885, 2022.
[14] B. Samdaengchai, S. Sinnung, P. Meena, T. Laosuwan, "An Analysis on Disasters caused by Flood via Data from Sentinel-1 Satellite", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 51, Vol. 14, No. 2, pp. 21-26, June 2022.
[15] I. Ounrit, S. Sinnung, P. Meena, T. Laosuwan, "Flash Flood Mapping based on Data from Landsat-8 Satellite and Water Indices", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 51, Vol. 14, No. 2, pp. 130-135, June 2022.
[16] C. Auntarin, P. Chunpang, W. Chokkuea, T. Laosuwan, "Monitoring and Analysis on Change of Land Surface Temperature based on Satellite Data", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 54, Vol. 15, No. 1, pp. 178-183, March 2023.
[17] B. Wiatkowska, J. Slodczyk, A. Stokowska, "Spatial-Temporal Land Use and Land Cover Changes in Urban Areas Using Remote Sensing Images and GIS Analysis: The Case Study of Opole, Poland", Geosciences, Vol. 11, No. 8, p. 312, 2021.
[18] M.S. Rana, S. Sarkar, "Prediction of Urban Expansion by using Land Cover Change Detection Approach", Heliyon, Vol. 7, No. 11, p. e08437, 2021.
[19] B. Hu, Y. Xu, X. Huang, Q. Cheng, Q. Ding, L. Bai, Y. Li, "Improving Urban Land Cover Classification with Combined Use of Sentinel-2 and Sentinel-1 Imagery", ISPRS International Journal of Geo-Information, Vol. 10, No. 8, p. 533, 2021.
[20] D. Druce, X. Tong, X. Lei, T. Guo, CMM. Kitte, K. Grogan, C. Tottrup, "An Optical and SAR Based Fusion Approach for Mapping Surface Water Dynamics over Mainland China", Remote Sensing, Vol. 13, No. 9, p. 1663, 2021.
[21] D. Xiang, T. Tang, Y. Ban, Y. Su, G. Kuang, "Unsupervised Polarimetric SAR Urban Area Classification Based on Model-based Decomposition with Cross Scattering", ISPRS Journal of Photogrammetry and Remote Sensing, Vol. 116, pp. 86-100, 2016.
[22] D. Amitrano, G.D. Martino, A. Iodice, D. Riccio, G. Ruello, "Urban Area Mapping Using Multitemporal SAR Images in Combination with Self-Organizing Map Clustering and Object-Based Image Analysis", Remote Sensing, Vol. 15, No. 1, p. 122, 2023.
[23] N.S. Lun, S. Chaudhary, S. Ninsawat, "Assessment of Machine Learning Methods for Urban Types Classification Using Integrated SAR and Optical Images in Nonthaburi, Thailand", Sustainability, Vol. 15, No. 2, p. 1051, 2023.
[24] A. Baquiran, T.B. Javier, R.J. Dalit, J.J. Manuel, D.J. Pacis, D.L. Palchan, E. Abana, J. Daliuag, "Mapping of Solar Power Potential Structures Using Geographic Information System", Engineering Research Bulletin, Vol. 8, pp. 5-9, 2020.
[25] H. Annette, H. Detlev, H. Carsten, K. Rolf, L. Elke, M. Richard, B.G. Hans, "Solar Energy Assessment using Remote Sensing Technologies", Remote Sensing of Environment, Vol. 86, No. 3, pp. 432-432, 2003.

[26] Y. Choi, J. Suh, S.M. Kim, "GIS-Based Solar Radiation Mapping, Site Evaluation, and Potential Assessment: A Review", Applied Sciences. Vol. 9, No. 9, p. 1960, 2019.
[27] M. Frackiewicz, "The Advantages of Synthetic Aperture Radar (SAR) Earth Observation Satellites", https://ts2.space/en/the-advantages-of-synthetic-aperture-radar-sar-earth-observation-satellites/, May 2023.
[28] L. Gruenhagen, C. Juergens, "Multitemporal Change Detection Analysis in an Urbanized Environment Based upon Sentinel-1 Data", Remote Sensing, Vol. 14, No. 4, p. 1043, 2022.
[29] Sentinel-1 SAR, "User Guide", https://sentinels.copernicus.eu/web/sentinel/user-guides/sentinel-1-sar, May 2023.
[30] F. Filipponi, "Sentinel-1 GRD Preprocessing Workflow", Proceedings, Vol. 18, No. 1, p. 11, 2019.
[31] S. Dahhani, M. Raji, M. Hakdaoui, R. Lhissou, "Land Cover Mapping Using Sentinel-1 Time-Series Data and Machine-Learning Classifiers in Agricultural Sub-Saharan Landscape", Remote Sensing, Vol. 15, No. 1, p. 65, 2023.
[32] J. Polo, R.J. Garcia, "Solar Potential Uncertainty in Building Rooftops as a Function of Digital Surface Model Accuracy", Remote Sensing, Vol. 15, No. 3, p. 567, 2023.
[33] D. Gawley, P. McKenzie, "Investigating the Suitability of GIS and Remotely-Sensed Datasets for Photovoltaic Modelling on Building Rooftops", Energy Build, Vol. 265, p. 112083, 2023.
[34] L. Breiman, "Random Forests", Machine Learning, Vol. 45, pp. 5-32, 2001.
[35] S. Niculescu, A. Billey, H. Talab-Ou-Ali, "Random Forest Classification Using Sentinel-1 and Sentinel-2 Series for Vegetation Monitoring in the Pays de Brest (France)", Proc. SPIE 10783, Remote Sensing for Agriculture, Ecosystems, and Hydrology XX, 1078305.
[36] S. Ibrahim, "Improving Land Use/Cover Classification Accuracy from Random Forest Feature Importance Selection Based on Synergistic Use of Sentinel Data and Digital Elevation Model in Agriculturally Dominated Landscape", Agriculture, Vol. 13, No. 1, p. 98, 2023.
[37] Defense Technical Information Center, "Projective and Object Space Geometry for Monocular Building Extraction", https://apps.dtic.mil/sti/citations/tr/ADA277586, May 2023.
[38] T. Hermosilla, L.A. Ruiz, J.A. Recio, J. Estornell, "Evaluation of Automatic Building Detection Approaches Combining High Resolution Images and LiDAR Data", Remote Sensing, Vol. 3, No. 6, pp. 1188-1210, 2011.
[39] S. Sangpradid, "Building Extraction from High Resolution Imagery", VRU Research and Development Journal Science and Technology, Vol. 9, No. 2, pp. 76-88.
[40] P. Fu, "A Geometric Solar Radiation Model with Applications in Landscape Ecology", University of Kansas: Lawrence, KS, USA, 2000.
[41] P. Fu, P.M. Rich, "A Geometric Solar Radiation Model with Applications in Agriculture and Forestry", Computers and Electronics in Agriculture, Vol. 37 pp. 25-35, 2002.
[42] P. Fu, P.M. Rich, "The Solar Analyst 1.0 Manual, Helios Environmental Modeling Institute (HEMI)", Lawrence, KS, USA, 2000.

BIOGRAPHIES

Name: **Aungkhana**
Surname: **Chompoosri**
Birthday: 30.06.1996
Birthplace: Chiangmai, Thailand
Bachelor: Geoinformatics, Faculty of Informatics, Mahasarakham University, Maha Sarakham, Thailand, 2019
Master: Student, Energy, Department of Physics, Faculty of Science, Mahasarakham University, Maha Sarakham, Thailand, Since 2021
Research Interests: Remote Sensing, Geographics Information System, Energy Technology

Name: **Satith**
Surname: **Sangpradid**
Birthday: 14.11.1976
Birthplace: Khonkaen, Thailand
Bachelor: Management Information System, Faculty of Science, Mahasarakham University, Maha Sarakham, Thailand, 1999
Master: Information Technology, Faculty of Information Technology, King Mongkut's University of Technology, North Bangkok, Thailand, 2003
Doctorate: Geoinformatics, Institute of Science, Suranaree University of Technology, Nakhon Ratchasima, Thailand, 2012
The Last Scientific Position: Assist. Prof., Department of Geoinformatics, Faculty of Informatics, Mahasarakham University, Maha Sarakham, Thailand, Since 2020
Research Interests: Machine Learning and AI, Natural and Environment Science, Geoinformatics, Carbon Sequestration, Information Science
Scientific Publications: 29 Papers

Name: **Wutthisat**
Surname: **Chokkuea**
Birthday: 04.05.1979
Birth Place: Buriram, Thailand
Bachelor: Applied Physics, Faculty of Science, Mahasarakham University, Maha Sarakham, Thailand, 2001
Master: Energy Engineering, Faculty of Engineering, Chiang Mai University, Chiang Mai, Thailand, 2005
Doctorate: Mechanical Engineering, Faculty of Engineering, Mahasarakham University, Maha Sarakham, Thailand, 2015
The Last Scientific Position: Assist. Prof., Department of Physics, Faculty of Science, Mahasarakham University, Maha Sarakham, Thailand, Since 2018
Research Interests: Renewable Energy, Energy Conservation, Energy Modeling
Scientific Publications: 9 Papers

Name: **Teerawong**
Surname: **Laosuwan**
Birthday: 02.10.1971
Birth Place: Songkhla, Thailand
Bachelor: Electronics Engineering, Faculty of Engineering, Southeast Asia University, Bangkok, Thailand, 1994
Master: Remote Sensing, Institute of Science, Suranaree University of Technology, Nakhon Ratchasima, Thailand, 1999
Doctorate: Electrical and Computer Engineering, Faculty of Engineering, Mahasarakham University, Maha Sarakham, Thailand, 2012
The Last Scientific Position: Assoc. Prof., Department of Physics, Faculty of Science, Mahasarakham University, Maha Sarakham, Thailand, 2015
Research Interests: Remote Sensing, Geo-Informatics, GIS modeling, Mobile Application Development, Energy Technology and Drone Surveying and Mapping
Scientific Publications: 104 Papers