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GIS-AHP Multi Criteria Decision Analysis for the optimal location of solar energy plants at Indonesia

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ABSTRACT

A reliable tool for site-suitability assessment of solar power plants capable to account for the protection of cultural, natural, and ecological conservation areas is proposed. The tool integrates an Analytic Hierarchy Process (AHP) based Multi Criteria Decision Analysis (MCDA) algorithm into a Geographical Information System (GIS) package, which consists of layers of satellite-derived data for energy resources and locally obtained data such as land usage, topography, community settlement, road lines, and electrical network, considered as the criteria layers for the assessment of site suitability. The study is focused on the West Kalimantan Province (WKP) which imposes significant challenges due to the wide diversification of protected areas that need to be considered, particularly in landmarks that demand for high resolution imaging of Global Horizontal Irradiation (GHI) within $\pm 4^{\circ}$ of the equator. To overcome these challenges, a GIS spatial weighted overlay analysis of criteria layers has been performed within three approximation schemes distinguished by the proximity to existing infrastructures. It has been found that although WKP has relatively high values of GHI over its entire area of $146,807\ km^2$, when the protected areas are accounted, only 34% of the area is available for solar power plant deployment. Further analysis using the AHP-MCDA approach, with consideration of the best-suitable conditions, significantly reduces the search of optimal location of solar power plants into just 0.07% to 0.03% of the WKP area. This corresponds to an area of $46.60 - 108.58\ km^2$ with an estimated generation capacity of $2,034 - 4,785\ MW$, what indicates that the abundant resources of WKP could be sufficient to meet the national renewable energy target. The results of this research should provide a model of decision support system for development of large-scale solar power plants in tropical countries, where the protection of forest and biodiversity is a global concern.

1. Introduction

Being the third largest island in the world and with a privileged location over the equator, the island of Borneo is considered as one of the richest landmasses for renewable power generation, and therefore attracting substantial attention from governments and investors onto the search of adequate routes for planning and exploitation of their solar energy resources. Politically divided among three countries, Brunei, Malaysia, and Indonesia, with the latter occupying up to 73% of Borneo's territory, Borneo Island offers a promising opportunity for energy inter-connectivity and energy sharing between the countries. It is the expectation of the Association of Southeast Asian Nations (ASEAN), that by 2030 the Indonesian territory of Kalimantan together with the two Malaysian states of Sarawak and Sabah, will have become a major energy resource center within an interconnected power network (Project 45076-001, 2014), benefiting of a strong intake of renewable energy resources (Gielen et al., 2017) for meeting the UN Sustainable Development Goals (SDG), i.e. Goal 7, to ensure access to affordable, reliable, sustainable and modern energy for all, with a specific target to substantially increase the share of renewable energy in the global energy mix by 2030 (UnitedNations, 2013). The state-owned energy provider Sarawak Energy is taking the lead on this milestone, according to the figures disclosed by the Ministry of Utilities of Sarawak last December 2019 in the Borneo's Sustainability & Renewable Energy Forum (Anon, 2019; Augustin, 2019), while there is no significant progress at the Indonesian side. In fact, the Indonesian situation is much critical than the Malaysian one, as just during the last five years Indonesia has imported about 200 million barrels of oil for the energy sector, with an approximate cost

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of 150 trillion IDR ($11.5 billion) yearly (Anon, 2018), resulting in a severe burden on the national budget whilst threatening the national energy security with compulsory power outages for under-developed communities (Tampubolon et al., 2019).

To reduce the dependency on fossil fuels, Indonesia has set a plan to increase the contribution of renewable energy in its energy mix by 2030, which aligns with the UN SGD. In the General Plan of National Energy (RUEN) issued by Presidential Decree in 2017, the power sector is targeted for the development of solar PV plants with capacity of 6.5 GW in 2025 and 14.2 GW in 2030 (Anon, 2017). To achieve this ambitious goal, solar PV plants are expected to be developed across 34 provinces in Indonesia, from which the Kalimantan region is expected to have a share of 1.081 GW in 2025, with 366.4 MW assigned to the West Kalimantan Province (WKP), 232.1 MW for East Kalimantan, 221.0 MW for Central Kalimantan, 160.0 MW for South Kalimantan, and 101.7 MW for North Kalimantan. Moreover, it is worth mentioning that between the different renewable sources available at Indonesia (Hasan et al., 2012), geothermal exploration in Borneo is not an option, as this is legally classified as a mining activity that can endanger the sustainability of protected and conservation areas (Kumar, 2016). The plan in RUEN was further implemented in more detail in the most recent Indonesia's 2019–2028 Electricity Procurement Plan (RUPTL) issued in 2019 by the Ministry of Energy and Mineral Resources in conjunction with national electricity company PLN (2020) and the Department of Population and Civil Registration (Sipil, 2019), which sets a minimum target of 1 GW solar power plant development per year until 2028. This is certainly a conservative figure given the average global horizontal irradiation (GHI) of 4.80 $kWh/m^2/day$ (Veldhuis and Reinders, 2015), which can render to a bare estimation of about 500 GW of solar power potential (Tampubolon et al., 2019).

The main challenge in achieving the target in solar energy development is the investment procurement that requires the identification of optimal locations where protected and conservation areas are not an impediment for the expansion of PLN grid (Hamdi, 2019; El-Katiri et al., 2019). The selection of optimal locations also should account for the limited grid-connection and poor transportation network, causing higher equipment delivery costs for the deployment of solar power farms, particularly in rural and remote areas where the energy demand is still high and the electrification ratio is low (Anon, 2018; Hamdi, 2019; El-Katiri et al., 2019; Rose et al., 2016). Additionally, the lack of an appropriate regulatory support system for the energy tariffs between different regencies, the unstable political and administrative coordination between local governments and stakeholders, and virtually non-existing tools for site-planing and land constraints identification, discourage investors on pursuing developing and planning permits as well as land acquisition bills for solar energy projects.

Given the privilege location over the equator and the proximity of the existing power network in the province and in the largest state of Malaysian (Sarawak), West Kalimantan Province (WKP) of Indonesia (see Fig. 1) provides a promising prospect for the development of large-scale solar power plants to meet Indonesian renewable energy target. Unfortunately, the development of solar power plants in the province is nearly stagnant. According to the latest report of PLN (Secretary, 2019), it currently has less than 0.1% of solar installed capacity (0.18 MW), within a total WKP generation capacity of 200.99 MW, from which more than 60% of it (123.03 MW) comes from Diesel powered generators. Furthermore, as noted previously, the development of solar power plants in this region presents a significant challenge as it should account for the protection tropical forests and biodiversity, which is a global concern as stated in the UN SDG, i.e. Goal 15, to protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss (UnitedNations, 2013).

Considering the above mentioned prospects and challenges, designing an adequate planning tool for the identification of optimal locations of solar power plants at WKP has been identified as a priority for the Indonesian government, and being the central subject of this paper which reports on the main results of the 2019–2020 British Council Newton Fund Institutional Links project "Solarboost" (Anon, 2020). In the project, we have counted with the active participation of major Indonesian stakeholders such as PLN (PLN, 2020), the Ministry of Energy and Mineral Resources ESDM (2020), the Regional Development Planning Agency BAPPEDA (2020), the Ministry of Environment and Forestry MENLHK (2020)), the Ministry of Agriculture PERTANIAN (2020), the Ministry of Public Works and Public Housing PUPR (2020), and Indonesian Meteorology Climatology and Geophysics Council BMKG (2020). These partners all have helped us into the conceptual design of our Geographic Information System (GIS) with an integrated Multi Criteria Decision Analysis (MCDA) tool based on Analytical Hierarchy Process (AHP). The planning tool allows the identification of optimal locations for solar power plants, based on a weighted overlay analysis of satellite retrieved high-resolution data of solar energy resources and climate conditions, over-layered with the relevant topographical, land use, community settlements, and electrical network data layers provided by our stakeholders at WKP. The tool is expected to support government and energy developers in the decision making processes, which ultimately helps to reduce the communication and administrative barriers that are currently impeding the successful deployment of the solar sector across the region.

Consequently, in this paper we present a comprehensive study about the main barriers that, within a data-oriented approach, must be incorporated into a GIS-AHP algorithm for the deployment of solar energy plants in landscapes with robust challenges as the ones encountered in the WKP at the Borneo Island. In processing all these spatial data, including vulnerability zones, protected and conservation land areas for analyzing the solar energy feasibility in WKP, in Section 2 we introduce a Multi Criteria Decision Analysis (MCDA) model integrated within an AHP algorithm which renders the analytical techniques for achieving higher effectiveness of GIS decision systems with multiple layers of information (see Fig. 2), in similar way to the recent works of H. Z. Al-Garni et al. on Saudi Arabia (Garni and Awasthi, 2017) and H. E. Colak on the province of Malatya in Turkey (Colak et al., 2020). Then, in Section 3 the results obtained from three different MCDA schemes are described, and the comparisons between their performances and subsequent implications are demonstrated, such that an optimal scheme and consequently an optimal area for the installations of solar power plants at WKP is disclosed. Finally, the main conclusions of this paper are presented in Section 4.

2. GIS-AHP-MCDA model framework

GIS-based Multi Criteria Decision Analysis (GIS-MCDA) techniques aided by AHP models for generating maps of potential areas for solar power plants development, in varying climate and topographic conditions, have been the subject of intense research during the last few years (Garni and Awasthi, 2017; Colak et al., 2020; Shorabeh et al., 2019; Giamalaki and Tsoutsos, 2019; Majumdar and Pasqualetti, 2019; Doorga et al., 2019; Yousefi et al., 2018; Doljak and Stanojević, 2017; Zoghi et al., 2017; Merrouni et al., 2016; Noorollahi et al., 2016; Kucuksari et al., 2014; Sánchez-Lozano et al., 2013; Uyan, 2013). However, a common factor between all this literature is that the availability

Fig. 1. Location map of the West Kalimantan Province (WKP) at Indonesia's Borneo.

of feasible sites for large scale solar farms deployment, highly determined by the different criteria that could have been selected in the study factors, and their corresponding weighting which are assigned within the AHP algorithm. Therefore, although there is no strict protocol in assigning weighting factors between the assessed criteria when these are not clearly linked by a known physical variable, like it is the case for GHI and its relation with the proximity of a solar farm with relevant local infrastructures (power network, roads, settlements, etc.), the assigning of relative weighting factors mostly depends on the decision of the researchers after their consultancy with relevant stakeholders and policymakers. To illustrate this, in Table 1 we present a brief comparison of some of the most relevant literature where different AHP weightings have been assigned to the same criteria according to the understanding of the authors of the local conditions and further constraints of the scrutinized area, as well as the state-of-the-art literature at the time of the publications (see Garni and Awasthi, 2017; Colak et al., 2020; Shorabeh et al., 2019; Giamalaki and Tsoutsos, 2019; Majumdar and Pasqualetti, 2019; Doorga et al., 2019; Yousefi et al., 2018; Doljak and Stanojević, 2017; Zoghi et al., 2017; Merrouni et al., 2016; Noorollahi et al., 2016; Sánchez-Lozano et al., 2013; Uyan, 2013 and references therein). Within this, we can see that regarding to the development of solar farms, the GHI is generally considered as the evaluation criteria with the greatest weighting factor, in particular when the area of a full country is being analyzed. However, when a better insight of the local climate, topology, energy-related policies, and the stakeholders interests is known, a larger weighting can be given to other particular criteria such as, for instance, the dust storms in Isfahan-Iran (Zoghi et al., 2017), or the proximity to the existing power grid in Cartagena-Spain Sánchez-Lozano et al. (2013). Therefore, if we want to provide a reasonable estimation of the criteria of interest and their corresponding weighting factors in a GIS-AHP algorithm for Borneo island, bearing in mind that ultimately this must be conceived as a platform aimed for the promptly use of solar energy investors and local policy-makers, we argue that the best and most sensible strategy is to focus the study first at a province level (e.g., at WKP), where decisions could be made promptly without encountering inter-regional administrative and political barriers.

In consequence, the present section of this study focuses on the formulated methodology for finding the optimal location or best suitable area for large scale solar power plants (> 5 MW), with special emphasis on the retrieved data from local information sources at WKP in Indonesia's Borneo. This enables the further consideration of vulnerability zones such as Borneo's conservation and land protected areas, as well as other information layers with relevant climate, topology, settlement, and proximity to infrastructure (roads and power grid) data, which are all together analyzed with respect to their spatial interrelationship with the local GHI map and its derived solar energy potential. In brief, a GIS-AHP MCDA method is employed to assign the rank and priority factors for the information layers aforementioned, where for the sake of simplicity and accessibility to any stakeholder, we have taken advantage of the recently introduced AHP Online Software (AHP-OS) by Goepel (2018), and then, a comprehensive spatial weighted overlay integration analysis is performed in ArcMap-GIS software (v10.6.1) following the overall methodology depicted in Fig. 2.

Firstly, concerning to the collection of data for the GIS-AHP MCDA platform, we are specifically interested in the West Kalimantan Province which extents between 2°08′ N and 3°02′ S, and between 108°33′ E and 104°10′ E, covering a total area of 146,807 km^2, with 14 major cities/settlements distributed across the province as show in Fig. 1. With the equator line crossing

Table 1
AHP weighting factors for different evaluation criteria extracted from the literature.

Evaluation criteria	Saudi Arabia (Garni and Awasthi, 2017)	Mauritius (Doorga et al., 2019)	Serbia (Doljak and Stanojević, 2017)	Isfahan Iran (Zoghi et al., 2017)	Iran (Noorollahi et al., 2016)	Cartagena Spain Sánchez-Lozano et al. (2013)
Solar radiation (GHI)	0.322	0.401	0.305	0.25	0.275	0.238
Sunshine radiation (daylight hours)	†	0.131	0.184	0.19	†	†
Air temperature	0.243	0.033	0.111	†	0.071	0.048
Relative Humidity	†	0.016	0.048	0.043	0.041	†
Elevation	†	0.021	†	0.059	0.081	†
Slope	0.163	0.194	0.153	0.042	0.08	0.112
Land Aspects/Use	0.108	0.046	0.077	0.066	0.07	0.116
Vegetation	†	†	0.122	†	†	†
Clouds/Snow/Rain/Dust conditions	†	†	†	0.254 0.101	†	
Proximity to Power Grid	0.085	0.093	†	0.05	0.112	0.415
Proximity to Road Infrastructure	0.046	0.065	†	0.032	0.088	0.043
Proximity to Settlements	0.032	†	†	0.014	0.081	0.028

† This criteria has either, not been considered within the cited study or it is not of relevance for the study location.

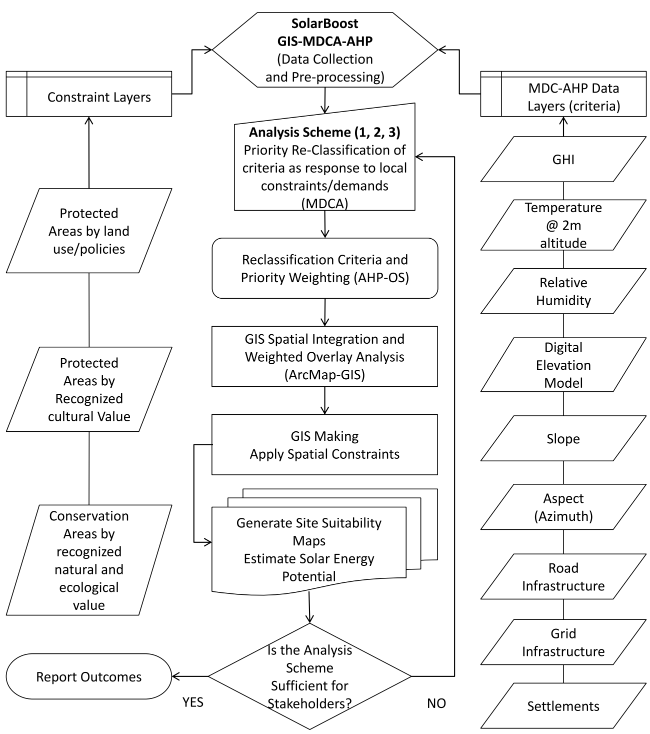

Fig. 2. Working flowchart of the GIS-AHP-MCDA platform developed for this study, which has been called SolarBoost to make reference to the funder's project identifier.

across this region the climate conditions of WKP are fairly uniform and ideal for the deployment of solar farms as reported by BMKG (2020), with a daily average of sunlight of 12 h and 7 min (sunrise ∼05 : 50, sunset ∼17 : 57), an annual average relative humidity of more than 90%, and a daily mean temperature at 2 m height which varies between 25.9 °C and 28.4 °C across the entire year. Therefore, daylight is not a criteria to be considered in this study as it will be irrelevant into a MCDA, but temperature and humidity are weighting criteria that still need to be considered, this mainly due to the fact that the efficiency of photo-voltaic (PV) cells and solar mirrors, both strongly depend on the variance of these two factors. However, as the annual mean temperature and relative humidity variance across WKP is almost negligible ($<$ 2%), they can be defined as a low priority criteria. Additionally, the WKP is benefited by a low slope topology which is ideal for minimizing aggregated costs of land leveling and flattering, both commonly required for the deployment of solar farms (Sabo et al., 2016, 2017), what makes also of this factor a low weighting criteria. Here, it is worth emphasizing that this study is not limited to PV farms but instead considers the whole solar energy prognostics, where other means of solar energy capture can be conceived such as solar thermal collectors. This explains why our study is focused on relatively large solar power plants ($>$ 5 MW) which are aimed to be connected to the main electrical grid, instead of off-grid approaches for small communities where roof PV-cells might be sufficient.

Likewise, in what concerns to the intensity of Global Horizontal Solar Irradiation, having chosen WKP as case of study is not an arbitrary decision as by analyzing the data recorded by Solargis and The World Bank Group (Program, 2017; Solargis, 2019), the highest potential of total global horizontal irradiation (GHI) per year is recorded in the city of Ketapang at the SE part of WKP (see Fig. 1) with 1742 kWh/m2/$year$. Nevertheless, this figure is subject to a maximum uncertainty of ±8% due to the high humidity level of the region, which adds another reason for which the humidity criteria needs to be accounted even if it has a low priority factor. Actually, the GHI, topology, and climatology data layers which can be collected from online public domains, all together serve as the base framework for any GIS-AHP MCDA model regardless of the location (see Table 1), but it is the local data provided by relevant stakeholders what can give an actual meaning and impact for choosing one or another MCDA-AHP scheme. In this sense, the different data layers collected from local stakeholders at WKP are summarized within Tables 2 and 3, where the full set of GIS criteria layers, sources of information, and mapping constraints are disclosed.

2.1. GIS constrained data layers

In a hierarchy process, all data layers mentioned in Table 2 are initially classified as secondary maps as these have to be preprocessed or digitalized for adequate rendering into the GIS platform. Thus, any non-spatial data collected from the different sources are converted into the spatial data and assigned UTM projection system, where north and south UTM grid zones must be considered for area calculations given that the WKP lies partially in both sides of the equator. Some of these data layers are considered as constraint layers as these involve protected land factors dictated by national and regional laws, where energy investments and related works might be undermined or simply prohibited by the sole existence of these factors. In particular, we have found that about 66% of the total land area of WKP (See

Table 2
GIS layers defining local constraints.

Data Layer	Source	Constraint
Settlement Location	Agency (2014a)	Settlement Proximity (Sp)
Power Grid	PLN (2020), Council (2019)	Grid Proximity (Gp)
Road Network[a]	Agency (2015)	Road Proximity (Rp)
Forestry Area	MENLHK (2020), Indonesian Ministry of Environment and Forestry (2014)	Protected area by law enforcement No. 733/2014 and no. 45/2004
Wildlife or Endangered habitat	Fund (2011)	Protected area by law enforcement No. 308/MENLHK/2019
Peatland	Indonesian Ministry of Environment and Forestry (2014)	Protected area by law enforcement No. 8599/MENLHK/2018
Cultural/Community Forest	Indonesian Ministry of Environment and Forestry (2014)	Protected area by law enforcement No.21/MENLHK/2019
Water bodies	Agency (2014b)	Protected area by law enforcement No. 38/2011
Rice field	of Agriculture (2012)	Protected area by law enforcement No.1/Perda Kalbar/2018

[a]Data retrieved in paper format.

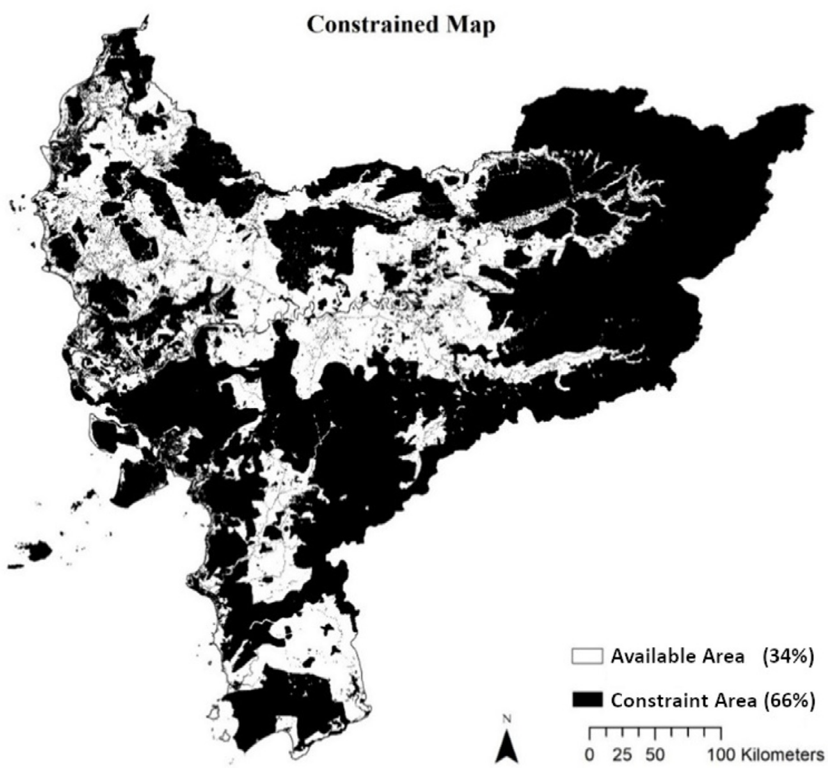

Fig. 3. Map showing the total calculated constraint region at WKP (in black), defining prohibited areas for solar farms deployment as reported in Table 2. Source Maps can be consulted at our created Web-Gis within the SolarBoost project (Anon, 2020) or by request to the author of correspondence.

Fig. 3) is subjected to legal constraints where any kind of developmental activities or inversion on these lands, different to the one originally intended, is heavily penalized by law enforcement due to their potential threat to the environmental and ecological equilibrium at local, national, or even global scale, as defined by the Indonesian government.

The constraint layers which are particularly defined by the enforcement of national or regional laws, and therefore demand liaison with relevant stakeholders (PLN, 2020; ESDM, 2020; BAPPEDA, 2020; MENLHK, 2020; PERTANIAN, 2020; PUPR, 2020; BMKG, 2020), or at least a comprehensive knowledge of relevant governmental laws and the local language, can be classified between different subgroups for easy GIS visualization (see Table 2). Between these, we can find: (i) Forestry Areas (Fig. 4A), which include factors such as production forestry (30.2% of WKP), protected forests (15.7%) and conservation forests (9.8%), (ii) Production and conservation weatlands (Fig. 4B), including rice fields (2.1%) and peatlands (4.2%), (iii) Protected cultural and community (Fig. 4C) forests (9.1%), (iv) Wildlife habitats (Fig. 4D) which account for water bodies (2.5%) and protected Orang-Utans habitats (19.9%), (v) Relevant infrastructure (Fig. 4E) such as, the major road network, and power transmission grid and, finally, (vi) the settlements which comprehend 0.4% of the WKP area (Fig. 4F). Thus, by overlapping all these data-layers, we have found that at least 66% of the total area must be extracted or constrained from the general GIS within MCDA-AHP (Fig. 3), in order to determine the optimal location for the installation or foreseeable deployment of solar power plants at WKP. However, it is important to mention that although other constraint layers belonging to relevant productivity areas at Indonesia could be included, such as oil palm and mining areas, these areas are not being included in this study as the current energy plans of the country aim for the reduction of its dependence on these sources (Anon, 2017; (PLN), 2019; Sipil, 2019), and furthermore,

Table 3
GIS-AHP-MCDA classification criteria layers subdivided into three major factors: (i) Climatology: GHI, Temperature, and Relative Humidity, (ii) Topography: Elevation, Slope, and Aspect, and (iii) Proximity factor: Power Grid, Road infrastructure, and Major Settlements.

AHP Factor	Source	Range	Class Range Δ	AHP Grading 1-9 Class Limits
GHI [kWh/m^2]	Solargis (2019)	$2.6 - 5.04$	0.28	Grade n = 1 to 9 class limits @ GHI= $2.6 + n * \Delta$
Temperature (T) [°C]	Solargis (2019)	$17.1 - 27.8$	1	Grade 1 class @ $T > 27.8$, Grade n = 2 to 8 class @ $27 - (n-1) * \Delta$ Grade 9 class @ $27 - (n-1) * \Delta$
Relative Humidity (H) [%]	NASA (2019)	$81.99 - 91.58$	1	Grade 1 class @ $H > 91$, Grade n = 2 to 8 class @ $91 - (n-1) * \Delta$ Grade 9 class @ $H < 84$
Elevation (DEM) [m]	for Spatial Information (CGIAR-CSI) (2020)	< 90	10	Grade n = 1 to 9 class limits @ $DEM = 90 - n * \Delta$
Slope (S) [%]	for Spatial Information (CGIAR-CSI) (2020)	< 9	1	Grade n = 1 to 9 class limits @ $S = n * \Delta$
Aspect Azimuth (A_z)	for Spatial Information (CGIAR-CSI) (2020)	WKP UTM Zones	N , NE E , SE S , SW W, NW	Grade 9 class @ , N(00-22.50) & S(157.50-202.50) Grade 5 class @ NE(22.50-67.50) SE(112.50-157.50) SW(202.50-247.50) NW(292.50-337.50) Grade 1 class @ E(67.50-112.50) & W(247.50-292.50)
Road Proximity (R_p) [km]	Agency (2015)	$0.1 \leq R_p \leq 10$	1.1	Grade n = 1 to 9 class limits @ $R_p = 10 - n * \Delta$
Power Grid Proximity (G_p) [km]	Council (2019)	$0.1 \leq G_p \leq 10$	1.1	Grade n = 1 to 9 class limits @ $G_p = 10 - n * \Delta$
Major Settlements Proximity (S_p) [km]	Agency (2014a)	$0.5 \leq S_p \leq 10$	1.055	Grade n = 1 to 9 class limits @ $R_p = 10 - n * \Delta$

these are not considered as protection or conservation areas as per the law.

2.2. GIS methodology for assessing AHP weighted data layers in the MCDA

To complement Table 3, it is worth mentioning that concerning the GHI and air temperature data, the World Bank Group (WBG) has already released average monthly datasets for 11 years (Solargis, 2019), where the monthly average deviation at WKP does not exceed the 7%, reason why singular (averaged) maps can be used for any of these factors, within this range of tolerance. Likewise, in order to interpolate the yearly average relative humidity data obtained as point data from NASA (2019), we have used the Kriging interpolation technique to generate spatial maps via the spatial analyst tools in ArcGIS 10.6.1 (Childs, 2014; Oliver and Webster, 1990). Also, we have used the Shuttle Radar Topography Mission Digital Elevation Model (STRM-DEM) retrieved from the CGIAR Consortium for Spatial Information (for Spatial Information (CGIAR-CSI), 2020), in order to prepare the ArcGIS topographical factor layers such as Elevation, Slope and Aspect maps. Thus, in Fig. 5 the spatial maps for all selected nine factors in Table 3, with their reclassified MCDA layers are shown, such that a further weighting system can be now invoked for enabling the AHP algorithm render towards a unique solution. However, as it has been mentioned at the introduction of this paper, assigning criteria factor layers and corresponding weights within an AHP algorithm is somehow a subjective process (see e.g., Table 1), as this strictly depends on the objectives of the researchers and, the extensive surveying of related literature. Thus, it results important to briefly relate why we have selected these nine factors as the most relevant criteria within the AHP algorithm, and how these are classified within a Grade-9 classification system.

Firstly, it is worth reminding that solar collectors and PV farms are both able to utilize diffused and direct solar radiation for electricity generation, where the total amount of incoming shortwave radiation received by a horizontal surface per unit time, i.e., the Global Horizontal Irradiation, GHI in kWh/m^2, is the chief governing factor to locate and identify the best site to install solar farms. In simple terms, the intensity of radiation and installation area determine the magnitude of the electrical output from a solar-power plant (Yang et al., 2019; Yushchenko et al., 2018; Program, 2017), where it is known that the exploitation of solar energy resources is economically viable or profitable, specially on locations with a GHI average of 4 $kWh/m^2/day$ (Hernandez et al., 2015, 2016). In this sense, at least from the GHI perspective, WKP is an ideal location as it attains an average of 4.58 $kWh/m^2/day$ measured across a 11 years by the WBG (Solargis, 2019), with really scarce days reporting minimums as low as 2.6 $kWh/m^2/day$ in small areas affected by short seasons of great cloudiness, but with maximums very often reaching up to 5.04 $kWh/m^2/day$ in the vast majority of the province. These figures have allowed us to reclassify the daily-averaged GHI factor layer into 9 grades (Table 3), with the GIS grading classes assigned by the post-processing of the original GHI map as shown in Fig. 5A. However, despite atmospheric factors are somehow considered within the GHI time-averaged classification above considered, and the cloudiness factor can be neglected due to the lack of solar-calendar seasons in WKP, this is not the only climatology factor of relevance for the integration of solar energy resources, as the energy conversion efficiency of these systems, in particular PV cells, strongly depend on the temperature and relative humidity conditions where they are installed.

According to the literature, on the one hand, the efficiency of state-of-the-art PV systems increases for temperatures lower than 25 °C, but at higher temperatures, every 1 °C rise leads to a decrease in the power output of 0.4%-0.5% (Doorga et al., 2019). Hence, areas with lower average temperatures are more favorable in the context of enhancing PV system performance, and consequently must be assigned the highest grading classification, where in the specific case of WKP (Table 3), the analysis of the data provided by the WBG have revealed that, in average, the daily temperature at sunlight hours ranges from 17 °C to 28 °C, with substantial areas which might influence negatively onto the making decision process for the deployment of PV farms (see Fig. 5B). On the other hand, the higher is the amount of relative humidity in an area the greater is the absorption of short wave solar radiation by surfaces moisture, which drops the total amount of incident solar irradiance usable by the solar panel (Abdo and EL-Shimy, 2013; Yang et al., 2020). Therefore, areas with high

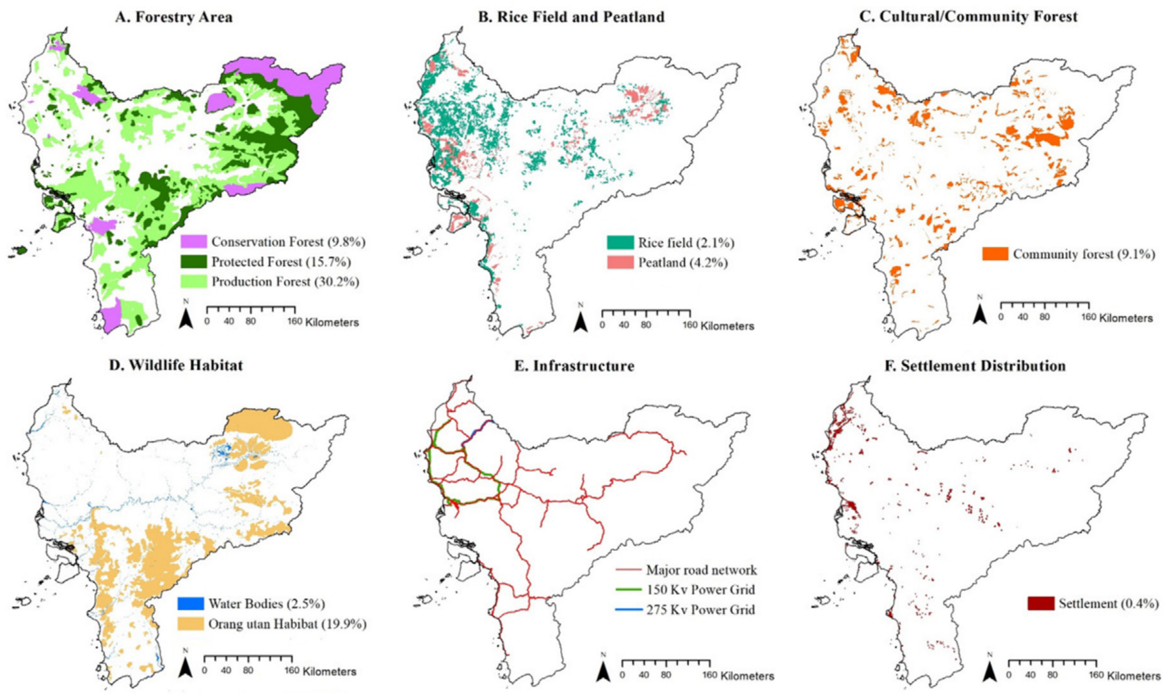

Fig. 4. Thematic maps used as constraint layers for site exclusions within the MCDA-AHP suitability analysis for the deployment of large scale solar PV plants in WKP. Source Maps can be consulted at our created Web-Gis within the SolarBoost project (Anon, 2020) or by request to the author of correspondence.

humidity are less prone to the exploitation of solar energy, corresponding thence to the lowest grade classes in our AHP model, with the opposite behavior for the highest classes (Table 3). This data was obtained at 130 locations across the WKP as point data from NASA (2019), which is then utilized for interpolating the yearly average relative humidity by using the spatial analysis Kriging interpolation technique in ArcGIS 10.6.1 (Childs, 2014) as mentioned above. This technique is a powerful interpolation method based on geostatistical techniques, which allows to predict the autocorrelation relationships among the measured points whilst affording a measure of spatial accuracy on the derived map (Oliver and Webster, 1990), from which we have obtained that the relative humidity in the WKP varies from 82% to 91.5% (see Fig. 5C). Additionally, as mentioned above, the topographical factors have been derived from the 30-m Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM) (for Spatial Information (CGIAR-CSI), 2020), whose processed dataset is further utilized to prepare the elevation, slope, and topographical aspect maps included in Fig. 5D–F. Therein, to reduce or even avoid the high expenditure derived from construction costs in high elevated and steep slope areas, the most favorable grade classes are given for land areas below 90 m in elevation, with flat or mild slopes ($<$ 9%), and with north/south facing slope (see Table 3).

Also, the proximity to infrastructure and settlement locations is considered as one of the major factors to be included into the GIS-AHP-MCDA algorithm, as these can have a strong impact on any technical economical feasibility study of solar plants. For instance, the greater is the distance between the prospective solar plant and the existing current transmission lines, the larger will be the investment value on related infrastructure as the costs associated to transportation of specialist goods and right of way could significantly increase (Doorga et al., 2019; Majumdar and Pasqualetti, 2019). Therefore, the highest-grade scale into the power-grid factor has been assigned for the areas closest to the 150 kV and 250 kV transmission lines at the WKP (Fig. 5G), with the latter being the one connected to Malaysian power grid, and where besides invoking the grading scheme shown in Table 3 with class variations within a range of 1.1 km, a buffer zone of 100 m has been assumed in order to ensure electrical safety when working near overhead power lines (Neitzel, 2016). Likewise, as the areas nearest to the major roads will avoid additional costs of transporting equipment during the construction and maintenance processes of a solar plant, a maximum radius of 10 km from road points has been considered by using the Euclidean Proximity method (Doorga et al., 2019), where we have added a buffer of 100 m from either side of major roads to reduce the levels of no-natural dust sources on which the solar panels could be exposed and, even the possibility of expansion of the road by increment of the carriageways of road lanes (see Fig. 5H). Then, the final factor to be considered is the proximity to settlements, where also a buffer of 500 m must be excluded from the calculations in order to reduce adverse environmental impacts on urban growth and population as suggested in Zoghi et al. (2017).

2.3. Implementation of the AHP

The Analytic Hierarchy Process (AHP) is a powerful tool for MCDA which uses ratio scale factors for pairwise comparison enabling the making of a judgment or decision from the weighting of several criteria (Sánchez-Lozano et al., 2013; Asakereh et al., 2017; Saaty, 1990, 2013). The pairwise comparison of different criteria makes AHP algorithms easy to adopt in complex GIS problems where spatial aspects can be considered by comparison of two different attributes at a time (Saaty, 2013; Malczewski, 2006, 1999), using standard grading classification ranges as the ones shown in Table 3. Consequently, our algorithm involves a pairwise comparison matrix for nine factors with pair relative importance ranks given by the 9-point likert scale shown in Table 4, from which the relative criteria weights have been obtained by the standard AHP priority-matrix normalization method (Saaty, 1990), and the AHP priority calculator introduced in Goepel (2018). For this purpose, the priority-matrix normalization method cannot be confused with the common definition of

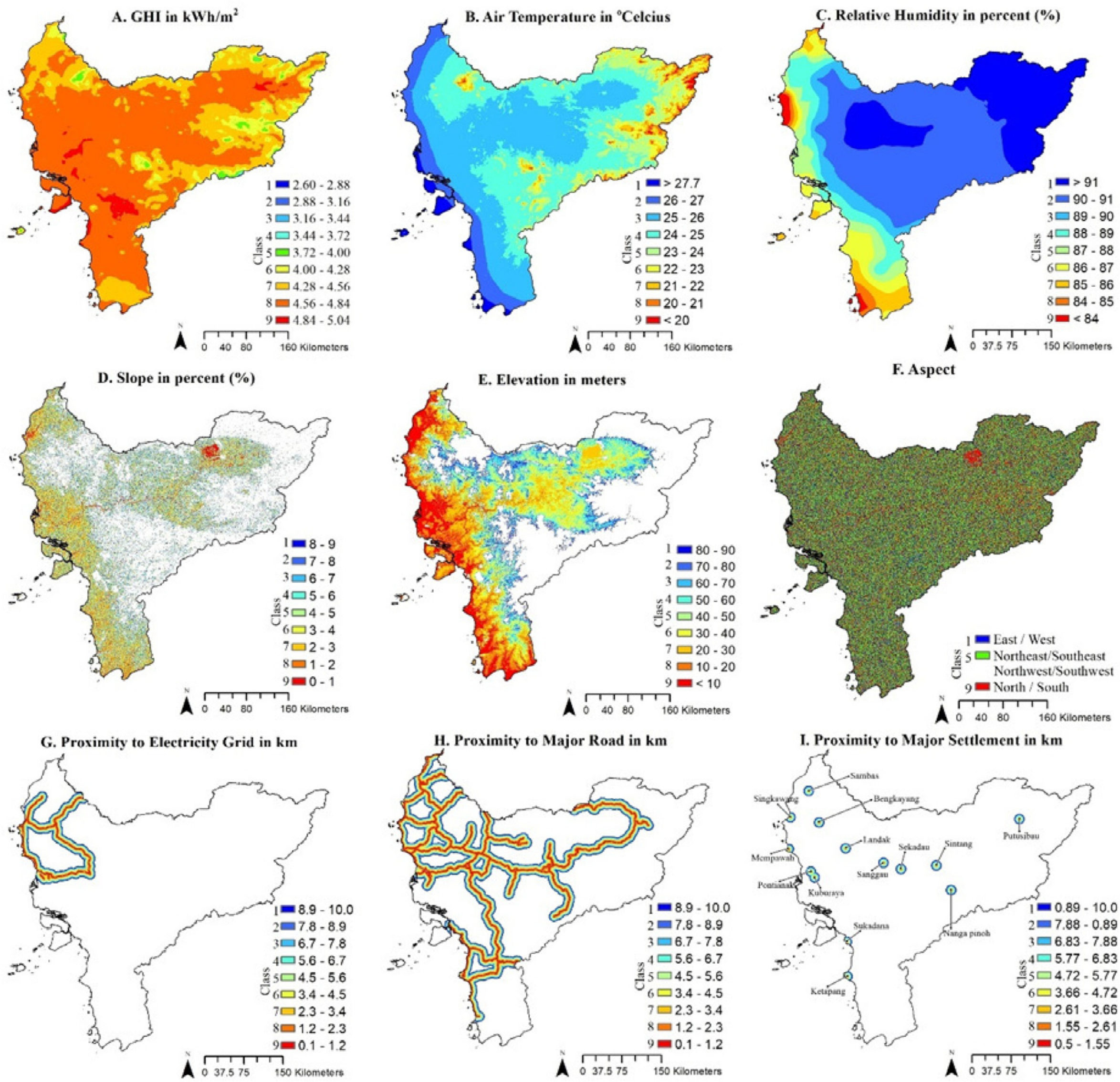

Fig. 5. Reclassified layers of input criteria as shown in Table 3, with grades ranging from class 1 with low suitable value (blue color) up to the class 9 (red color) referring to maximum suitability conditions for the deployment of solar power plants. Source Maps can be consulted at our created Web-Gis within the SolarBoost project (Anon, 2020) or by request to the author of correspondence. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

matrix normalization in linear algebra, as in the AHP method the priority-matrix has to be normalized by dividing each assigned numerical value with the sum of values in the belonging column of the AHP priority calculator and then, the average for each row in the matrix is calculated following the strategy adopted in Doljak and Stanojević (2017), which specifically applies for the MCDA of solar plants development based upon GIS-AHP algorithms.

Then, in order to check the consistency of the decision maker's pairwise scores, we have calculated the consistency ratio, $CR = CI/RI$, where the consistency index (CI) is defined by:

$$CI = \frac{\lambda_{max} - n}{n - 1}\,, \tag{1}$$

with λ_{max} the eigenvalue of the pairwise comparison matrix and n the criteria number, where the random consistency index values, RI, for the n values have been considered from Saaty (2013).

Thus, to obtain meaningful results with the AHP technique within our GIS-MCDA calculations, we have ensured that for all the analyzed cases the CR is less or equal to 5%, otherwise the pairwise comparison values are recalculated for improving the factors weighting consistency. This can be seen in Table 5 where different prioritization schemes or MCDA approaches have been taken for all the nine factors within the three major considered criteria, i.e, climatology, topography, and proximity to location, being the latter the one which has a greater influence in the search for an optimal location of solar power plants, it due to the fact that the time and spatial variance of the climatology and topography factors have shown a negligible impact on their pairwise comparison with the GHI factor, as it will be shown by the sensitivity analysis shown in the following section. Consequently, the results presented in this paper are reduced to three fundamental approaches, these based upon the proximity of the solar plant to (1) the power network, (2) the road infrastructure, and (3) the community settlements, where the factor weights reported in Table 5, resulted in consistency ratios of, CR = 4.2%, 4.1%, and 4.5%, respectively.

Table 4
AHP pairwise likert grading criteria scale used for the GIS-MCDA algorithm.

Grading criteria	Grade definition by relative importance	Description (Ranges)
1	Equally important	Both criteria contribute equally to the objective (within the CR)
2	Mildly low	Both criteria nearly contribute equally to the objective or, slightly favor one criterion over another (within CR and 12.5%)
3	Moderately low	The contribution moderately favor one criterion over another (within 12.5% and 25%)
4	Low	The contribution has a low tendency to favor one criterion over another (within 25% and 37.5%)
5	Medium	The contribution has a medium tendency to favor one criterion over another (within 37.5% and 50%)
6	Mildly high	The contribution has slightly higher than the medium tendency to favor one criterion over another (within 50% and 62.5%)
7	Moderately high	The contribution of one criterion over another is moderately high (within 62.5% and 75%)
8	High	The contribution of one criterion over another is high (within 75% and 87.5%)
9	Extremely high	The contribution of one criterion over another is at the highest in the grade (greater than 87.5%)

Table 5
Criteria and Factor weightings for the three discussed AHP approaches, each with the highest weight given either to the distance to (1) the power network, (2) the road infrastructure, or (3) the community settlements.

Criteria	AHP Factor	Factor weighting by approach			Aggregated criteria weight by approach		
		1	2	3	1	2	3
Climatology	GHI	0.250	0.222	0.158	0.355	0.344	0.265
	T	0.086	0.093	0.086			
	H	0.019	0.029	0.021			
Topography	DEM	0.026	0.030	0.027	0.114	0.150	0.128
	S	0.052	0.071	0.058			
	A_z	0.036	0.049	0.043			
Proximity to Location	G_p	0.272	0.0	0.0	0.531	0.506	0.607
	R_p	0.148	0.351	0.339			
	S_p	0.111	0.155	0.268			

3. Results and discussion

It is shown in the top row in Fig. 5 that WKP has relatively high values of GHI over the entire its area of 146,807 km^2. If only the GHI is considered as the governing factor onto the making decisions process, it is easy to visualize that more than 98% of the WKP could be considered as a technically suitable area for the installation of solar power plants. However, the technically suitable area is not entirely exploitable as the exploitation of protected cultural, natural, and ecological conservation areas must be avoided. By excluding the GIS layer mapping the lands with conservation or protected status (Fig. 3), the available area for solar power plant development is significantly reduced to 34%. The exclusion of the protected areas is important for the sustainable development, not only for development in WKP but also development in the world. As shown in Fig. 4, the excluded forestry area covers 55.7% of WKP's area. Protection of the forestry in tropical region, as it is the case of WKP, is really urgent due to the profound influence of tropical forest on weather patterns, freshwater, natural disasters, biodiversity, food, and human health, which affects not only the countries where forests are found, but also the distant countries (Brandon, 2014). It was reported that tropical deforestation is responsible for 10.3 billion tons CO_2 equivalent of global greenhouse gas (GHG) emissions each year, which is about twice the total GHG emissions for the United States (IPCC, 2013). This shows the significant contribution of tropical deforestation on global climate change, and therefore the conservation of tropical forest attract a quickly growing attention of international communities.

Although the exclusion of protected areas significantly reduces the search area for the installation of solar power plants and simultaneously reduces the likelihood of finding legal barriers that could stop the investment on this technology, this simplified approach still presents significant challenges in terms of the grid-connectivity and technical deployment of solar farms. Therefore, as general rule, the topographical criteria must be considered as the secondary AHP factors, which in the case of WKP (middle row in Fig. 5), and in general of Borneo island. This produce a nearly negligible impact onto the assessment of optimal locations of solar power plants, due to the fact that nearly all locations at Borneo show relatively the same Aspect conditions (relative to sun light), and the slope and elevation factors in non constrained areas (at least in WKP) show little variance on the suitability grading. Thus, in order to provide a sensible map of optimal locations for the installations of solar power plants at WKP, which goes beyond the already comprehensive task of compiling the large set of local information for defining exclusion areas, we address the relevance of the proximity factor under the three approaches discussed above (Table 5). The highest weighted factors are given to the shortest distances between the aimed location for the deployment of a solar plant and (1) the power transmission network, (2) the major roads, and (3) the settlements (see bottom row at Fig. 5). Then, as the GHI across WKP has been proven to be quasi-steady and generally high along the whole year, the GHI factor is always assigned the second priority rank after the proximity factor, assuring a feasible amount of solar irradiation for a profitable energy production at a prospective location. Therefore, in order to simplify the analysis of the derived spatial maps from these approaches (Fig. 6), the weighted overlay analysis of GIS layers have been grouped into four suitability categories with the "less suitable class" including the grades 1 to 3 from Table 3 and then, the "moderately suitable", "suitable", and "best suitable" classes, each grouping the grades 3 to 5, 5 to 7, and 7 to 9, respectively. Likewise, a detailed summary of the estimated areas for the optimal location of solar power plants with and without the exclusion of constrained areas is included in Table 6.

Also, it is worth noticing that depending on the technology for the conversion of solar energy and the GHI value at the chosen region, the required area for the production of a MW of power can vary (Gastli and Charabi, 2010). In this sense, the yearly electric power generation potential (GP) at the WKP has been estimated from:

$$GP = SR \times CA \times SF \times \eta \times 365\,, \tag{2}$$

where SR is the annual averaged daily GHI in kWh/m^2/day, CA defines the available or suitable land area for the deployment of solar farms in m^2, SF is the so-called shading factor which is an indicative measure of what fraction of the calculated areas is exploitable for PV panels (or any other solar conversion system), and η is the solar power conversion efficiency of the system called. In this sense, we have assumed a shading factor of 0.7 based on the maximum fraction of land that can be covered with PV solar panels with minimum shading effect (Gastli and Charabi, 2010), and a PV panel conversion efficiency of $\eta = 16\%$ as a representative figure of the average efficiency of commercial silicon PV modules (Doorga et al., 2019).

The results of analysis, as shown in Table 6, indicates that the scheme with high priority on proximity to power network (approach 1) results in the lowest value of "best-suitable" area, while the scheme with high priority on proximity to road infrastructure (approach 2) results in the highest value of "best-suitable" area. It is worth to note that the analysis using the AHP-MCDA approach, with consideration of the best-suitable conditions, significantly reduces the search of optimal location of solar power plants into just 0.03% to 0.07% of WKP area. This corresponds to area of 46.60–108.58 km^2 with an estimated generation capacity of 2034–4785 MW, which indicates the abundant resources of WKP to meet the national renewable energy target. In the case of approach 1, when only technical aspects are considered, the "best-suitable" area is reduced to only 0.16% of the WKP (230.59 km^2), while when the protected areas are taken into account, the exploitable "best-suitable" area is significantly reduced to 0.03% of the WKP (46.60 km^2). Considering the estimated generation capacity of 43.65 MW/km^2, exploitation 18% of the "best-suitable" area ($\sim$8.39 km^2) is sufficient to meet the national target of solar power plant development of 366.4 MW for the WKP, as planned in RUEN (Anon, 2017). However, achieving the target would demand a considerable investment by PLN and possibly by other energy stakeholders. In fact, being the national owned company PLN the major energy stakeholder in Indonesia, we have found that their current electricity supply business plan as described in RUPTL ((PLN), 2019) lacks of sufficiently documented plans for solar energy capable to meet the RUEN targets. That is why the disclosing of suitable PV deployment areas within well documented approaches, as the ones implemented in this study, are expected to promote the development of local policies aimed to help the country to achieve its national targets. Moreover, given the relatively homogeneous GHI and topographical profiles across non-constrained areas at WKP (see Figs. 2 & 3), and actually of what is expected of any non-constrained area at national level, the estimated PV generation capacity of 43 MW/km^2 is not expected to change, that could allow other provinces to set up analogous policies.

In fact, even if the less suitable areas at WKP are considered, i.e., those within the suitability classes 1–3 (21537 km^2), the calculated PV daily generation capacity does not vary substantially (43.37 MW/km^2). This leads to nearly the same area needed for meeting the RUEN target ($\sim$8.44 km^2), but with the expense of possibly increasing the infrastructure costs controlled by the proximity between the solar farm and the current settlements and roads infrastructure. Thus, a much larger room for the deployment of solar power plants is foreseeable if the suitability scale considers as well the classes 5–7, rendering to an exploitable area of about 2615.42 km^2 (1.78% of WKP), that (in average) corresponds to areas within 3.3 km and 4.5 km of distance between the solar plant and the existing power network (see Table 3). However, the drawback of this approach is that it implies that the "suitable" and "best suitable" classifications will restrict the development of solar power plants only around the northwest of WKP, where the main power transmission network and major cities are located, deprecating the development of further routes of commerce and communities at the central, east, and south regions of the WKP. Still, within the approach 1 these areas are somehow covered by the classes 3–5, which are considered as regions "moderately suitable", showing the impact of considering the proximity to the roads as a major factor within our GIS-AHP-MCDA algorithm. Nevertheless, if beyond the upgrading of the existing power grid the government decision is to extend or to increase the current capacity of the transmission network, covering then the communities above mentioned, the power grid itself which already collides with some major roads becomes irrelevant, and consequently the derived map under the approach 1 (Fig. 6A) could deliver an incorrect message to policy-makers. Therefore, for the development of a new power network sustained by solar power plants, a more refined approach is still required.

Based in the observations above, and by noticing that the electricity grid is also at the proximity to major roads connecting the cities of Sambas, Singkawang, Menpawah, Pontianak, Kuburaya, Landak, and Bengkayang (see bottom row of Fig. 5), it is possible to center the proximity to location criteria to only the factors of Road Proximity, R_p, and Settlement Proximity, S_p as shown in the approaches 2 and 3 of Table 5. Within these strategies, is then important to re-assess the weighting criteria for each one of these factors, such that comparison between the different schemes is viable, by ensuring that the same or nearly the same consistency ratio is obtained as mentioned in Section 2.3. Thus, in the approach 2, the R_p is given the highest priority followed by the GHI, as this will be the most natural approach to take, keeping similar ratios for the other factors as established in the approach 1. In this way, we have found that the "best suitable" unconstrained sites for the deployment of solar power plants can be in an area as large as 437.18 km^2 (0.3% of the WKP), which is a bit less than twice the unconstrained area obtained within the approach 1. However, by excluding the constrained regions we have found that the total exploitable area (108.58 km^2) is actually of about 2.33 times greater than the one obtained with the approach 1, which is an excellent result as this now covers the eastern and southern areas of the WKP that were not deemed as "best suitable" in the approach 1.

Nevertheless, a couple of issues arise with the interpretation of the GIS map derived by the approach 2, as although the settlement locations in Fig. 5I could be easily identified to be at the center of the denser "best suitable" areas (large red dots), with these and the classified "suitable" areas within approximately 20 km from the main road network, there are also "moderately suitable" regions which are much more than 20 km far away of the settlements, the current roads and, the power grid infrastructures, a fact which will considerably rise the cost of development of a solar power plant. Thus, despite these areas could be considered as good locations for new settlements and further expansion of the WKP communities, if a better classification of suitable and best suitable sites for the deployment of solar farms is to be given to policy makers, investors, and other stakeholders, an additional

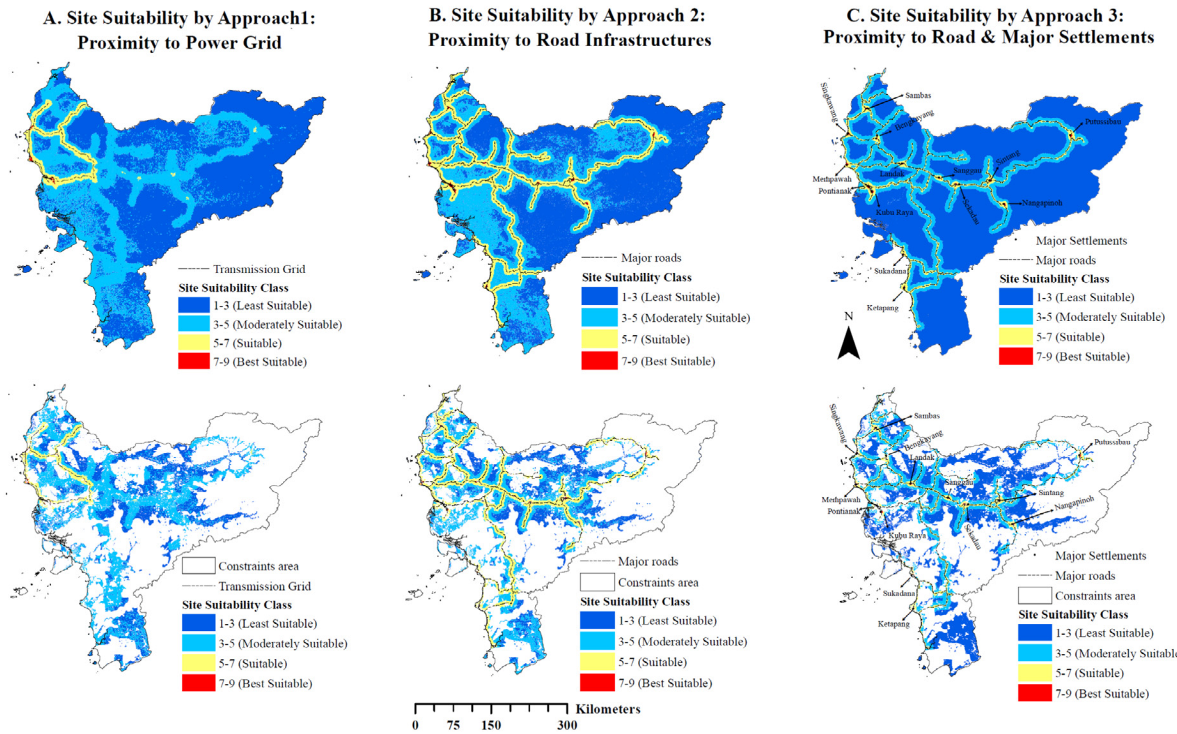

Fig. 6. Spatial map showing suitability sites for large-scale deployment of solar farms at WKP before (top pane) and after (bottom pane) excluding the constraints' layer shown in Fig. 3, under the approaches (1) proximity to the power grid (left pane), (2) proximity to road infrastructure (middle pane), and (3) proximity to roads and settlements (right pane). Class legends must be read with the highest numerical level being non-inclusive, otherwise included.

Table 6
Full and exploitable areas for the deployment of solar power plants according to the obtained maps in Fig. 6. Results are given in km^2 (top rows) and WKP-relative percentage (bottom rows). All numerical values under the referenced approaches are given in the mentioned units, respectively.

	Approach 1 [km^2]		Approach 2 [km^2]		Approach 3 [km^2]	
Suitability Class	Full 146807	Exploitable 48523	Full 146807	Exploitable 48523	Full 146807	Exploitable 48523
1–3	92260.59	21537	74101.12	14568.91	107338.7	27780.22
3–5	48985.62	24323.86	51877.56	22339.82	29815.7	15787.68
5–7	5330.2	2615.42	20391.15	11506.28	9278.1	4874.5
7–9	230.59	46.60	437.18	108.58	374.5	80.79
	Approach 1 [%]		Approach 2 [%]		Approach 3 [%]	
	Full 100	Exploitable 33.05	Full 100	Exploitable 33.05	Full 100	Exploitable 33.05
1–3	62.84	14.67	50.47	9.92	73.11	18.92
3–5	33.37	16.57	35.34	15.22	20.31	10.75
5–7	3.63	1.78	13.89	7.84	6.32	3.32
7–9	0.16	0.03	0.30	0.07	0.26	0.06

approach where greater weight is to be given to the proximity to existing settlements needs to be pursued.

Consequently, in the approach 3 we have increased the relative weighting of the S_p factor, at the expense of reducing the importance of the GHI due to the established isomorphism of this condition. This resulted in a most refined suitability map, where not only the "best suitable" exploitable area which in average covers the grade classes 7 — 9 in Table 3, and the corresponding "suitable" ones for the classes 5–7, both approximately double the solar exploitation areas obtained within the approach 1, thereby including the largely dependent communities on diesel-powered electricity such as Sintang, Sanggau, Nanga Pinoh, Sukadana, and Ketapang, but also present a clearer and most systematic distinction on what accordingly with Tables 3 and 6 can be considered as the regions of WKP which are moderately or least suitable for the deployment of solar power plants.

The total annual electric power generation capacity at the WKP has been also calculated before and after excluding the constraint conditions for each one of the three approaches above considered (see Table 7). This shows the large effect that the consideration of protected and conservation areas imply on measuring the energy potential at the diverse regions of Borneo Island, and how the classification of priority criteria can render to largely different predictions. Still, we have demonstrated the enormous potential of Borneo island in what concerns to solar energy production, as a proper planning of solar power plants just at the WKP could be sufficient to meet the 2030 clean energy plans of Indonesia ((PLN), 2019; Sipil, 2019). Moreover, regardless on the plans of the Indonesian government, either by expanding the current power transmission network to supply and connect the cities or settlements largely dependent on fossil energy production, or to upgrade the existing power transmission network for achieving a better and more competitive interconnection with the Malaysian power grid at the North-west of the WKP, we have found that a common factor within the three adopted approaches is that the optimal site for the deployment of solar power plats resulted in locations proximate with the city of Mempawah, therefore, also close to the cities of Pontianak and Singkawang, with an average exploitable area of 3019 hectares and annual solar energy production capacity of 6.63 TWh. Likewise, the nearby of the city of Putussibau at the eastern side of WKP is also highlighted, as the approaches 2 and 3 have allowed us to identify about 1689 *Ha* (average) as the best suitable locations for solar power plants, which could be better positioned than the "best suitable" areas closer to the cities of Sintang, Sanggau, Sekadau, Nanga Pinoh, Sukadana, and Ketapang, given its good road connection and proximity with the major AH150 road at Malaysia.

Finally, for concluding the MCDA process, it is important to conduct a sensitivity analysis of the GIS-AHP outcomes, such that a policy or decision maker can give suitable references onto the influence of each input criteria and associated priority factors in the attained suitability maps. Generally, AHP results are highly sensitive to the weighting criteria and prioritization factors which depend directly on the specific objectives of the research involved or the aims of particular stakeholders (Garni and Awasthi, 2017; Doorga et al., 2019), which therefore implies that there is not a unique method for defining a sensitivity analysis which could not be seen, somehow, biased towards one or another factor. However, a systematic sensitivity analysis can be performed by excluding individual input criteria in the AHP analysis, such that the influence of this particular criteria can be quantified from the GIS-AHP suitability maps obtained, as long as the chief criteria is maintained across the entire study, i.e., the GHI data layer in our case. Thus, as by excluding a specific input criteria into the AHP algorithm, the sensitivity analysis demands to keep the relative weightings of the other criteria unchanged, then, due to possible changes in the pairwise comparison system, a small fluctuation ΔS in the AHP weightings appears (Kumar, 2016; Doorga et al., 2019), which can be accounted by

$$\Delta S_{i,j} = \frac{S_{i,j} - S_j}{S_j} \times 100\% \,, \qquad (3)$$

where ΔS_i^j is the percentage change in the jth site suitability class due to the exclusion of the assessed ith input criteria in Table 3, with $i \neq j$, and $S_{i,j}$ and S_j the corresponding suitability class areas (see Fig. 6) with and without the exclusion of the ith input criteria.

Thus, as all criteria with exemption of the GHI can be omitted, the remaining 8 AHP factors are individually assessed, with the resulting sensitivity values being shown in Table 8. The results indicate both positive and negative changes in the percentage areas for the specific suitability classes, i.e., increments or decrements of the calculated areas due to the exclusion of individual input criteria, respectively. In particular, it is to be noticed that starting from the approach 1, and by excluding the proximity to the power grid factor, G_p, the area originally classified as "best suitable" increases in only a 14.66%. This is due to the now larger influence of the other two proximity factors, road infrastructure and settlements' location, which as a matter of fact have a much lower impact in the GIS area calculations. Consequently, a large increment in the other classification areas, i.e., those called as "moderately suitable" and "suitable" would be seen as a result of the larger areas covered by the topography and climatology factors, which in average tend to benefit the western side of the WKP (See Table 5 & Fig. 5). This explains then, why by excluding the proximity to the road factor, R_p, both extremes of the GIS-AHP map classification, i.e., the least and best suitable areas, both result reduced in about 50% the originally calculated areas (see Table 6), as the moderately suitable area will be now predominately defined by the G_p and S_p factors. This makes the areas closer to the settlements and the current power transmission network to be more favorable for the deployment of solar farms, but at the expense of possible considerations in the expansion of the power network to the large number of settlements currently dependent of power-diesel generators, as previously discussed. Moreover, if the S_p factor is the one to be excluded, then finding an optimal location for the development of a solar farm could be more biased, as regardless of the inherent social and economic development implications that this decision might imply, the "best suitable" area would increase in more than 400% the original found area, which is not precisely a better result from the technical and investor points of view, as farther is the distance between the power network at the transmission level to the settlements, as larger will need to be the power distribution-level network that will need to be created. Consequently, although the sensitivity analysis presented in Table 8 allows to quantify in a simple manner the influence of the different GIS-AHP weighted factors into the present MCDA, it also reveals why the three approaches presented across this paper focus mainly on the strong dependence of the proximity criteria, as generally the GIS-AHP-MCDA implemented at the WKP is less sensitive to changes onto the climatology and topography factors.

4. Conclusions

In line with global efforts to achieve the UN SDG in the field of energy, Indonesia has set a plan in RUEN to increase the share of renewable energy to 28.6% by 2030, in which the development of solar power plants is targeted to reach 14.2 GW. The development of large-scale solar power plan is required for achieving the target, in which the determination of optimal location of solar power plant is essential. In this paper, we have presented the development of a reliable tool for site-suitability assessment of solar power plants capable to account for the sustainable development and protection of cultural, natural, and ecological conservation areas, as the results of the 2019–2020 British Council Newton Fund Institutional Links project "Solarboost". The research was focused the West Kalimantan Province (WKP) of Borneo Island in Indonesia, mainly due to the promising prospect of international energy inter-connectivity and the urgency of protection of tropical forest and biodiversity in Borneo for sustainable world development.

The tool was developed by integrating an Analytic Hierarchy Process (AHP) based Multi Criteria Decision Analysis (MCDA) tool into a geographical information system (GIS) package consists of layers of satellite-derived data of climate conditions and locally obtained data such as land usage, topography, community settlement, road lines, and electrical network, that are considered as the criteria layers for the determination of optimal sites for the development of solar power plants. The solar energy resource and climate conditions have been obtained from a single averaged maps that have been created from the set of 11-years monthly derived GHI and air temperature data provided by the World Bank Group. Likewise, the yearly average relative humidity map has been obtained as point data from NASA, where we have used the Kriging interpolation technique to generate spatial maps via the spatial analyst tools in ArcGIS 10.6.1. Topography factors such as elevation, slope, and aspect have been obtained with the STRM digital elevation model from CGIAR. The data of local information have been provided by our local partners such as PLN, the Ministry of Energy and Mineral Resources, the Regional Development Planning Agency, the Ministry of Environment and Forestry, the Ministry of Agriculture, the Ministry of Public Works and Public Housing, and Indonesian Meteorology Climatology and Geophysics Council.

Table 7
Projected annual PV energy generation potential at the full and exploitable areas of WKP accordingly with Eq. (2) and the results obtained in Table 6 for the three approaches adopted in this study (see Fig. 6). All numerical values under the referenced approaches are given in TWh/*year*.

	Approach 1 [TWh/*year*]		Approach 2 [TWh/*year*]		Approach 3 [TWh/*year*]	
Suitability Class	Full 27530.18	Exploitable 9261.67	Full 27534.56	Exploitable 9247.31	Full 27541.30	Exploitable 9253.48
[1–3]	17106.25	4090.97	13648.14	2758.76	20022.66	5287.95
[3–5]	9365.94	4663.51	9909.41	4271.06	5671.83	3015.33
[5–7]	1014.01	498.28	3892.90	2196.54	1774.81	934.59
[7–9]	43.98	8.91	84.11	20.96	72.00	15.62

Table 8
Percentage sensitivity factor ΔS_i^j as described by Eq. (3), with the $i-$input criteria defined as in Tables 3 and 5.

	ΔS_i^j [%]			
Excluded criteria - i	$j =$ Least Suitable	$j =$ Moderately Suitable	$j =$ Suitable	$j =$ Best Suitable
T	6.60	−12.60	−0.95	234.62
H	3.53	−6.83	2.05	29.88
DEM	10.01	−19.08	−2.18	10.53
S	5.80	−11.79	2.54	50.82
A_z	8.99	−17.57	−2.61	101.40
G_p	−95.94	148.63	315.50	14.66
R_p	−54.73	105.94	−7.87	−52.86
S_p	−42.38	77.27	11.18	471.64

For the determination of optimal location of solar power plants AHP-MCDA was applied with three approximation schemes distinguished by the proximity to the existing (i) power network, (ii) road infrastructure, and (iii) community settlements. It has been found that although WKP has relatively high values of GHI over the entire area of 146,807 km^2, when the protected areas are taken into account, only 34% of the area is available for solar power plant deployment. The exclusion of the protected areas is highly important, considering that 55.7% of WKP's area is covered by the protected forestry, which has the profound influence on weather patterns, freshwater, natural disasters, biodiversity, food, and human health, which affects not only Indonesia, but also other countries in the world. Application of AHP-MCDA approach with the best-suitable conditions significantly reduces the search of optimal location of solar power plants into just 0.03% to 0.07% of WKP area. This corresponds to area of 46.60–108.58 km^2 with an estimated generation capacity of 2034–4785 MW, which indicates the abundant resources of WKP to meet the national renewable energy target. By estimating the generation capacity of 43.65 MW/km^2, we found the exploitation of area of ($\sim$8.39 km^2) is sufficient to meet the national target in RUEN, in which the solar power plant development in WKP is targeted to reach 366.4 MW in 2030.

Although the three approaches considered in this paper have render to the estimation of highly suitable areas for the deployment of solar power plants at WKP, where a stakeholder could give a conscious preference to one or another factor, we argue that from our single perspective, our third approach allows a better or clearer inclusion of settlements with electricity networks largely dependent on diesel generators, such as the ones at the towns of Sintang, Sanggau, Nanga Pinoh, Sukadana, and Ketapang. The approach also presents a clearer and systematic distinction onto the diverse suitability levels when the region is heavily subject to non-physics or legally based constraints. This has shown the large effect that the consideration of protected and conservation areas imply on measuring the energy potential at WKP, and consequently on the diverse regions of Borneo Island.

The results of this research is expected to reduce the main barrier in the development of large-scale power plants in WKP, and potentially extended to other provinces in Indonesia, that would result in significant increase of renewable energy contribution to support the sustainable development of Indonesia. Furthermore, the developed tool should provide a model of decision support system for development of large-scale solar power plants in tropical countries, where the protection of forest and biodiversity is a global concern.

Declaration of competing interest

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

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