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Multi-Attribute Decision-Making: Applying a Modified Brown–Gibson Model and RETScreen Software to the Optimal Location Process of Utility-Scale Photovoltaic Plants

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Received: 7 July 2019; Accepted: 31 July 2019; Published: 2 August 2019

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Abstract: Due to environmental and economic drawbacks of fossil fuels, global renewable energy (RE) capacity has increased significantly over the last decade. Solar photovoltaic (PV) is one of the fastest-growing RE technologies. Selecting an appropriate site is one of the most critical steps in utility-scale solar PV planning. This paper aims at proposing a rational multi-criteria decision-making (MCDM) approach based on the Brown–Gibson model for optimal site selection for utility-scale solar PV projects. The proposed model considers the project's net present value (NPV) along with seven suitability factors and six critical (constraint) factors. The RETScreen software was applied in calculating the NPV, the simple payback period and the carbon emission savings of the project at each alternative site. The weights of the suitability factors were determined using the analytical hierarchy process. Applied to the case study of finding the best location for a 5 MW solar PV project in northern Cameroon, the optimization results showed that Mokolo was the optimal location. The sensitivity analysis results revealed that the rankings of alternative sites based on the project's NPV and the proposed model are not consistent. Compared to the traditional MCDM approaches, the proposed model provides decision-makers with a more practical thinking method in the optimal location process of utility-scale solar projects.

Keywords: renewable energy; photovoltaic; Cameroon; RETScreen; optimal location; multi-criteria decision-making (MCDM); Brown–Gibson model; analytic hierarchy process (AHP)

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1. Introduction

Energy, especially electricity, has long been recognized as an essential commodity for everyday life in the contemporary world [1]. It is the main driving force of the human, social, and economic development of any nation. According to the International Energy Agency (IEA), the global electricity generation in 2017 was 25,551 TWh, of which fossil fuels (coal, oil, and gas) accounted for up to 65% [2] as illustrated in Figure 1 of the 2017 global electricity generation mix. However, due to their non-renewable nature, these sources are not likely to satisfy the increasing world demand in electricity resulting from the permanent growth in the world's population and technological advancement. They are declining steadily. A study by Abas et al. [3] showed that oil, natural gas, and coal would be depleted in 2066, 2068, and 2126, respectively. This situation is the primary cause of the current price volatility and energy supply insecurity. Furthermore, the burning of fossil fuels releases toxic air pollutants and greenhouse gases (GHGs), which are detrimental to health and contribute to climate change. The consequences of climate change are far and varied, and include increased wildfires, prolonged droughts, stronger tropical storms, and frequent coastal floods [4].

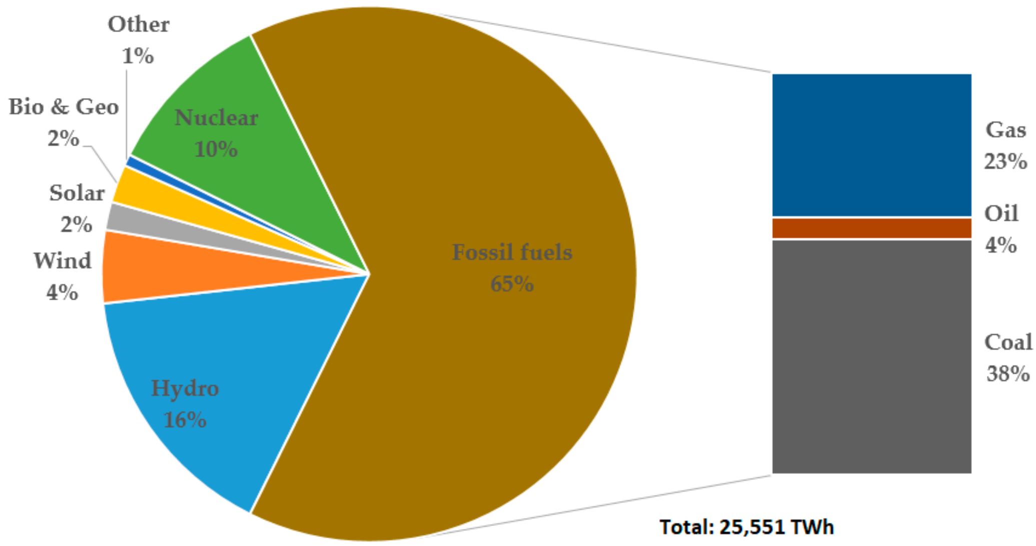

Figure 1. Electricity Generation Mix 2017 (Data from [2]).

The two disadvantages mentioned above constitute the foremost drivers of the development of renewable energy sources (RESs) which have the advantage of being inexhaustible, free, locally available, and environmentally friendly. RESs include solar photovoltaic, solar thermal, wind energy, hydropower, wave power, biomass, and geothermal. In 2017, with a newly installed global capacity of 178 GW (9% addition over 2016), renewables accounted for 70% of net increases to global power capacity [5].

With 99 GW newly installed capacity in 2017, solar photovoltaic led the way, accounting for about 55% of newly installed renewable power capacity. From 2007 to 2017, the global solar photovoltaic capacity increased from 8 GW to 402 GW, as depicted in Figure 2 of the 2007–2017 global photovoltaic capacity [5]. China led the five top countries for cumulative solar PV capacity with 131 GW, followed by the United States (51 GW), Japan (49 GW), Germany (42 GW), and Italy (19.7 GW) [6]. This dramatic expansion of solar photovoltaic is mainly due to its growing competitiveness, combined with government incentives and regulations.

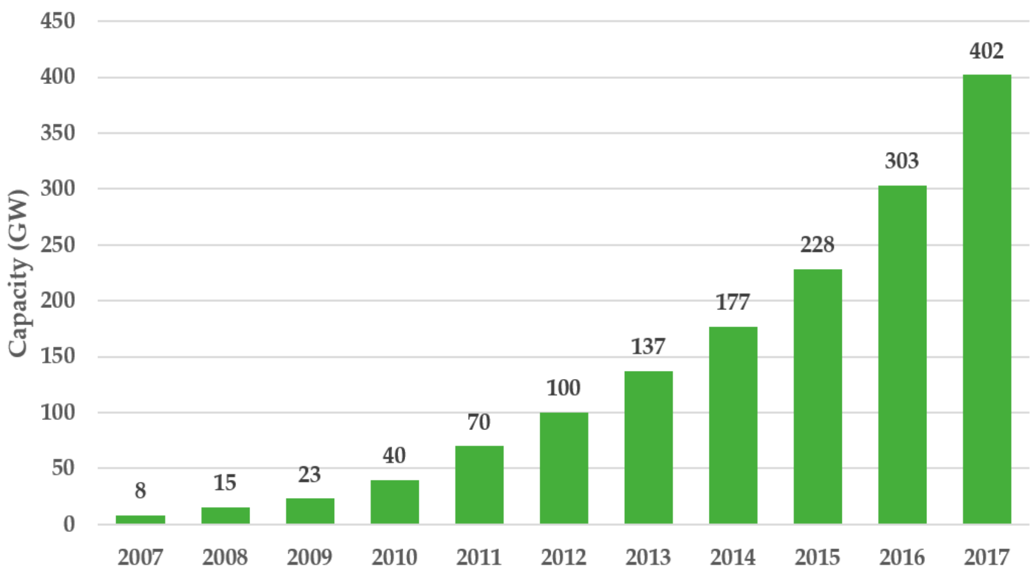

Figure 2. 2007–2017 global photovoltaic capacity (Data from [5]).

However, Africa, and particularly the sub-Saharan region is on the sidelines of the current expansion of photovoltaic technology. In 2017, the cumulative total installed capacity in solar PV in the region was only 3060 MW, i.e., less than 1% of the global capacity. Furthermore, these capacities were only installed in a few countries. South Africa (1714 MW), Algeria (400 MW), Reunion (189 MW), and Egypt (96 MW) accounted for nearly 80% of solar PV capacity in Africa [7]. Consequently, solar photovoltaic is at its infancy in most African countries. The African continent is endowed with enormous untapped potential for solar resources. Its theoretical potential for photovoltaic energy has been estimated at 660 petawatt hours per year (PWh/year), considering a PV module efficiency of 16.5% [8,9].

Most African countries have adopted solar PV as the primary renewable energy technology to face their electrification challenges. This is the case in Cameroon, where the importance of solar PV has been highlighted in the 2011's electricity law. The electricity supply in Cameroon is characterized by a low per capita consumption. In 2016 it was only 266 kWh, which was very low as compared to the 4000 kWh in South Africa or the 13,000 kWh in the USA [10]. Furthermore, there are still 9 million people without access to electricity, which leads to a national electricity access rate of 62%, unequally distributed between rural areas (23% access rate) and urban areas (92% access rate) [11,12]. The power outages are frequent, causing visible damages to households and industries. The average duration of power outages in industries was evaluated at 35 h/week [13]. The industrial companies are then forced to resort to self-generation of power through thermal generators. The installation of utility-scale grid-connected PV plants could allow grid extension and improve the quality of power. Several utility-scale PV projects, such as the construction of 500 MW solar photovoltaic facilities by JCM Greenquest Solar Corporation, have been announced. The search for sites conducive to the implementation of projects is a decisive step in the planning and effective take-off of solar PV technology in Cameroon.

The optimal location process for solar PV projects requires the investigation of a broad set of objectives and balancing multiple targets to determine the best sites. Existing literature shows that numerous approaches have been applied to find the optimal location for utility-scale photovoltaic installations. Among them, two classes are more recurrent: those using software tools and those using multi-criteria decision-making (MCDM).

The review of solar PV simulation software tools was carried out in several papers [14–16]. These software tools include, among others, RETScreen, HOMER Pro, PV F-CHART, PVPLANNER, SYSTEM ADVISOR MODEL (SAM), and PVSYST. The principle of using these tools in site evaluation consists mainly of determining and comparing techno-economic criteria (Net Present Value (NPV), Internal Rate of Return (IRR), Benefit-Cost Ratio (BCR), SPP (Simple Payback Period), capacity factor, electricity generation, etc.) of a hypothetical solar photovoltaic plant at different sites to be evaluated. The studies that used those tools include the analysis performed by Bustos et al. [17] who used RETScreen software to assess the techno-economic performance of a 30 MW on-grid solar PV system with a two-axis tracking system at 22 locations in Chile. Jain et al. [18] and Asumadu-Sarkodie and Owusu [19] used the same software to perform a techno-economic analysis of a fixed 5-MW grid-connected solar PV system at 31 sites in India and 20 sites in Ghana respectively. Samu and Fahrioglu [20] and El-Shimy [21] did the same for a 5-MW grid-connected system at 28 sites in Zimbabwe and 29 sites in Egypt respectively, while Kebede [22] employed both RETScreen and HOMER to evaluate 35 locations in Ethiopia, considering a 5 MW grid-connected solar PV system at each site.

Simulation software tools help decision-makers and project designers classify different sites according to the techno-economic performance of a hypothetical PV plant. However, their main drawback is that they do not take into account certain key factors that could affect the relevance of the sites and even make the project unfeasible. These factors include among others, social factors (public acceptance, impact on the ecological environment, and impact on surrounding businesses), climatic factors (dusty days, sunshine, solar radiation, rainy and snowy days), local environmental factors (agrological capacity, land use, and land cover), and orography factors (slope, orientation, elevation, and plot area) [23].

Unlike simulation software tools, MCDM methods for site selection of utility-scale solar PV systems can integrate all the criteria mentioned above into the decision-making process. MCDM techniques differ in their respective characteristics and data requirements as well as in the objectives of the decision-makers. These methods include among others, the Weighted Linear Combination (WLC), Elimination and Choice Translating Reality (ELECTRE), Analytical Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Multi-Choice Goal programming (MCGP), Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE), VIšekriterijumsko KOmpromisno Rangiranje (VIKOR), and ideal point methods. Literature reviews on MCDM applications in the RE planning are provided in [24,25].

Generally, the international scientific community has endorsed AHP as a flexible and robust MCDM tool to address the complexity of decision-making problems [26]. Often coupled with (GIS) or other MCDM methods, AHP applications in site selection for utility-scale solar PV projects is the most used MCDM approach [23]. It has been successfully applied in site selection for solar PV plants in Ismalia, Egypt [27]; Konya region, Turkey [28]; Ayranci region, Turkey [29]; Eastern Morocco [30]; and Limassol, Cyrus [31]. Table 1 provides a summary of these studies. Two types of criteria were considered in these studies: restriction factors (or constraint) factors and evaluation criteria. The constraint factors are those that prevent the implementation of utility-scale PV projects at the site if they are not satisfied.

The main limitation of MCDM approaches as applied so far for the selection of utility-scale PV sites is that they do not consider financial or technical criteria such as the NPV, IRR, SSP or capacity factor of the solar PV systems in the decision-making process. These pieces of information are however crucial for the decision to implement a utility-scale PV project at a site. Most often, simulation software tools provide them. Consequently, developing an MCDM model integrating the output of a simulation software tool will help to deal with the disadvantages of traditional MCDM approaches and software tools for the selection of utility-scale PV sites. To the best of the authors' knowledge, such a model has never been developed in the literature.

The main objective of this study is to propose an MCDM method based on a modified Brown–Gibson model for the selection of utility-scale PV sites from a given set of alternatives, through a rational decision-making process, taking into account the criteria of traditional MCDM approaches as well as output from the RETScreen software simulation. The proposed method is applied to the case of a 5 MW PV plant in northern Cameroon.

The rest of the paper is structured as follows: Section 2 describes the materials and methods adopted to realise the study. Section 3 presents the results obtained and discussion. The paper ends with a conclusion in Section 4. All acronyms used in the paper are given in Table A1 in Appendix A.

Table 1. Selected multi-criteria decision-making (MCDM) related studies for the selection of photovoltaic (PV) solar sites.

Ref. Year	Location	Constraint Factors	Criteria Category	Evaluation Criteria
[27], 2013	Ismailia, Egypt	Buffer of urban areas = 2.000 m Buffer of roads s = 200 m		• Distance to power line (m) • Distance to main road (m) • Distance to urban areas (m)
[28], 2013	Konya region, Turkey	Buffer of residential areas = 500 m Buffer of rivers and lakes = 500 m Buffer of roads = 100 m Buffer of protected areas = 500 m	Environmental factors	• Distance from residential areas • Land use
[29], 2017	Ayranci region, Turkey		Economic factors	• Slope (%) • Distance from roads • Distance from transmission lines
[30], 2018	Eastern Morocco	Buffer of residential areas = 2.000 m Buffer of rivers and lakes = 500 m Buffer of roads and railways = 100 m Buffer of agricultural areas = 500 m	Climate	• GHI (kWh/year/m^2)
			Orthography	• Slope (%)
			Location	• Distance from residential (km) • Distance from road (km) • Distance from electricity grid (km)
			Water resource	• Distance from water ways (km) • Distance from dams (km) • Distance from groundwater (km)
[31], 2016	Limassol, Cyrus	Buffer of urban areas = 200 m Buffer of natural forest = 200 m Buffer of roads and railways = 50 m Buffer of shoreline = 200 m Buffer of waterway = 100 m Buffer of archaeological site = 500 m	Technical	• Elevation • Slope • Solar radiation
			Social	• View-shed from primary roads
			Financial	• Land value • Distance from road • Distance from the power grid

2. Materials and Methods

Figure 3 illustrates the flowchart of the proposed methodology. A hypothetical 5 MW PV plant is considered.

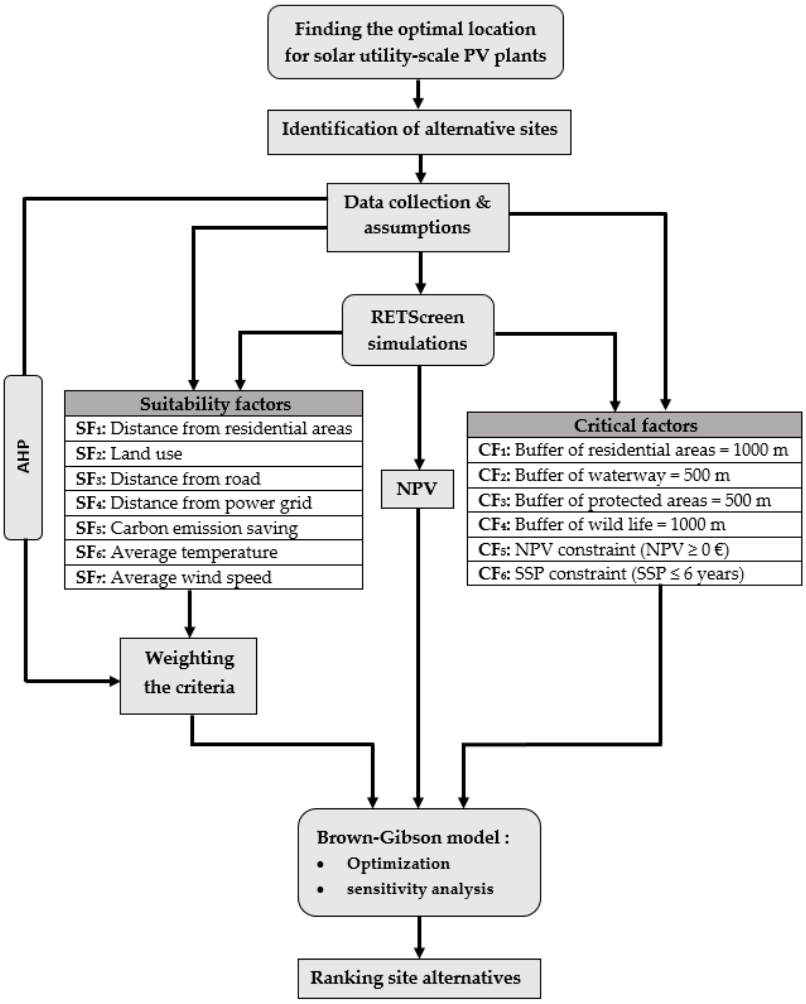

Figure 3. The flowchart of the adopted methodology for the study.

Some of the criteria used in the modified Brown–Gibson model were calculated using RETScreen software. These criteria include the carbon emission savings, NPV, and SPP of the hypothetical PV plant at each site. The weights of the suitability factors were computed using the AHP (Analytical Hierarchy Process) method. The collection of the data was done through literature review, Google Earth, NASA website, and ArcGIS.

All analyses were performed on Windows 10 Pro 64-bit with 2 GHz Intel Core i7 CPU, 8 GB of RAM, and 3 GB GPU. The following sections provide a thorough explanation of the materials and methods involved in this paper.

2.1. *The Area of the Study and Selected Alternative Sites*

The map of the area under study is presented in Figure 4. This area is covered by the NIG (Northern Interconnected Grid) which includes the Adamawa, North, and Far-North regions. Three reasons guided this choice: (1) the area is one of the poorest parts of the country; (2) its access to electricity is quite low (only 48% against 88% in the rest of the country), and (3) the area has the highest solar potential in the country.

Figure 4. Map of the study area.

Twelve locations were selected as alternative locations for the analysis. The only selection criterion was the availability of data from the NASA database. The selected locations are listed as follows: Banyo (1), Garoua (2), Maroua (3), Meiganga (4), Mokolo (5), Mora (6), Ngaoundéré (7), Poli (8), Tcholoré (9), Tibati (10), Tignère (11), and Yagoua (12).

The average daily solar radiation (ADSR), average yearly temperature (AYT), and average yearly wind speed (AYWS) of each location were collected from the NASA database. The distance from residential areas (DRA), distance from protected areas (DPA), distance from wildlife (DWL), and distance from the road (DR) of each site were measured using Google Earth. The latter was also used to obtain information about land use (LU) of each location. The distance from the power grid (DPG) was measured using an ArcGIS map of Cameroon's electricity transmission grid available online [32]. The coordinates of the alternative sites and their respective attributes are shown in Table 2.

Table 2. Alternative sites 'coordinates and their respective attributes.

Location	Latitude (N)	Longitude (N)	Elevation (m)	ADSR (kWh/m^2/d)	AYT (°C)	AYWS (m/s)	DRA (m)	DPA (m)	DWL (km)	DR (m)	DWW (m)	LU [1]	DPG (m)
Banyo	06°45′41″	11°47′22″	1115	5.44	23.1	2.8	622	8050	17,000	2032	3005	2	10,541
Garoua	09°16′46″	13°22′06″	209	5.75	26.7	3.5	1800	1600	20,502	1700	1890	3	5300
Maroua	10°34′34″	14°19′00″	403	5.70	27.7	3.8	1706	7125	8585	700	2412	2	4058
Meiganga	06°30′35″	14°18′40″	992	5.55	23.6	3.2	450	8805	48,522	600	968	2	4521
Mokolo	10°45′11″	13°49′53″	779	5.74	26.6	3.7	2302	10,582	35,074	1052	1250	3	3589
Mora	11°03′23″	14°06′53″	454	5.82	28.1	3.9	2000	65,000	58,840	2504	2350	3	3100
Ngaoundéré	07°20′04″	13°34′06″	1102	5.62	24.1	3.3	2155	12,055	175,458	950	1568	4	2944
Poli	08°28′46″	13°15′13″	613	5.75	25.8	3.4	1917	65,232	41,778	1980	495	4	9745
Tchollíré	08°23′26″	14°08′56″	393	5.74	26.2	3.4	2514	28,541	8741	1105	1985	2	4895
Tibati	06°27′02″	12°38′02″	873	5.64	23.3	3.2	1560	1755	2587	824	2585	2	8650
Tignere	07°22′38″	12°38′24″	1181	5.59	24.7	3.2	1534	10,811	7584	562	1368	1	6582
Yagoua	10°19′51″	15°14′33″	337	5.76	28.6	3.9	1159	1852	2558	1502	2522	2	5680

ADSR: average daily solar radiation; AYT: average yearly temperature; AYWS: average yearly wind speed; DRA: distance from residential areas; DPA: distance from protected areas; DWL: distance from wildlife; DR: distance from the road; LU: land use; DPG: distance from the power grid; DWW: distance from water way. [1] 1 for forest, 2 for Cultivated land, 3 for pasture, and 4 for bare land/desert.

2.2. PV System Configuration and Specifications

The proposed utility-scale system in this study is a hypothetical 5-MW grid-connected PV plant with no storage and no load as presented in Figure 5. It should be noted that 5 MW is the minimum size for a utility-scale solar PV plant [18–22], hence the most appropriate size for the first large-scale solar PV projects in Cameroon where such projects have never been implemented.

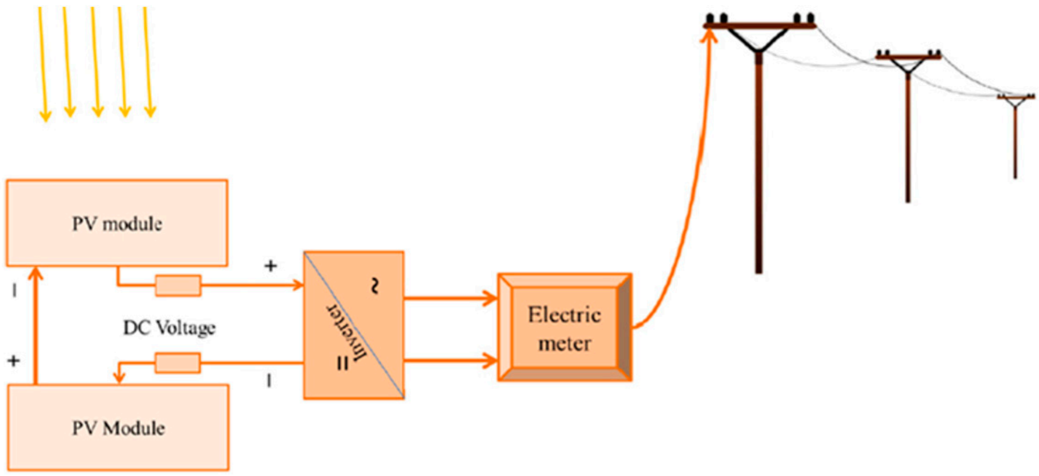

Figure 5. The overview of the proposed solar PV system.

The two main components of the system are the solar photovoltaic modules and the inverter. PV modules consist of connected cells. The modules are, in turn, connected in strings to generate the required direct current (DC) power from solar radiation through the photovoltaic effect in a soundless, clean, and static process. The inverter is required to convert the DC power into the alternating current (AC) power. The obtained AC electricity is measured by an electric meter before being exported to the utility grid.

The Sunpower SPR-320E-WHT-D module was selected for the analysis. It is a 320-W monocrystalline silicon module. This module had already been considered for PV related studies in Ghana [19] and Zimbabwe [20]. Table 3 displays the specifications of this module.

Table 3. Specification of the PV module [19,20].

Item	Specification
Manufacturer	Sunpower
PV Module type	Mono-si
Module number	SPR-320E-WHT-D
Module efficiency	19.60%
Power capacity	320 W
Dimensions	32 mm × 155 mm × 128 mm
Maximum system voltage	DC 600 V
Operating temperature	−40–80 °C
Area	1.60 m^2
Weight	18.60 kg

Fifteen thousand six hundred and twenty-five modules, constituting a total solar collector area of 25,000 m^2, are required for the considered 5-MW capacity of the system. These modules were considered to be mounted on a one-axis tracking system, inclined at the latitude angle of each site and facing the south. The azimuth angle was considered to be zero for all alternative locations.

A recent report by the US National Renewable Energy Laboratory (NREL) [33] indicates that the inverter efficiency has reached 98% at the current level of the technology. The same report estimates the optimal PV/inverter sizing ratio for grid-tied systems at 1.3. Consequently, a 3.9-MW capacity was required for the inverter of the proposed PV plant.

2.3. RETScreen Analysis

RETScreen is an Excel-based software package developed in 1996 by the Natural Resources Canada's Canmet Energy Research Center towards providing low-cost pre-feasibility analysis of renewable energy projects. RETScreen model uses a computerised system with integrated mathematical algorithms for assessing energy production, financial viability, life-cycle costs, and GHG emission savings potential for different types of renewable energy technologies (RETs) following a top to bottom approach [34]. It has the advantage of requiring fewer data and less computing power. HOMER, for example, uses global solar radiation levels (GSR) for one year, requiring 8760 individual values, while RETScreen uses average monthly GSR levels with only 12 values [35]. Independent reviews demonstrated that RETScreen could be used to carry out the calculation of energy production from energy systems with a relative error of less than 6% [36]. Further information about RETScreen and its operational mode is provided in the literature [37–39].

The role of RETScreen software in this study was twofold. Firstly, it was applied to compute the NPV, capacity factor, and the carbon emission of the selected utility-scale PV project at each location, to be used as part of the inputs for the Brown–Gibson location model. Secondly, it helped perform scenario-based techno-economic analyses of the selected project at the selected site.

The version used for the analyses in this study is RETScreen 4. The system requirements for this version include Microsoft Windows XP or higher, Microsoft Excel 2003 or higher, and Microsoft NET Framework 4 or higher.

The input data for solar radiation of each alternative location were collected from the NASA Surface meteorology and Solar Energy (SSE) database [44]. The techno-economic input data required for the RETScreen analyses in this study are presented in Table 4. Oil was considered as the fuel type in the baseline scenario for the calculation of greenhouse gas emission savings.

Table 4. Techno-economic input data for the analyses with RETScreen [33,40–43].

Parameters	Units	Value Used
Inflation rate	%	1.5
Project lifetime	yr	20
Debt term	year	10
Debt ratio	%	70
Discount rate	%	10
Debt interest rate	%	15
Electricity export rate	€	100
Total initial costs of PV	€/kW	1661
O and M of PV	€/kW/year	13.12
Inverter capacity	kw	3900
Inverter replacement cost	€/kW	51
Inverter efficiency	%	98
Inverter lifetime	year	15
Miscellaneous losses	%	5
T & D losses	%	10
Transmission line cost	€/km	5000

2.4. Brown–Gibson Model

2.4.1. The Original Model

The Brown–Gibson model is a single-site and multi-attribute model developed by P. Brown and D. Gibson in 1972 [45], primarily to address the disadvantages associated with qualitative and quantitative methods. It is a well-elaborated model which considers three classes of criteria or factors, namely critical factors, objective factors, and subjective factors. Critical factors are those that determine whether a location will be considered for further evaluation. Non-compliance with a critical factor prevents the plant from being set up at a site, although other favourable conditions may exist. Objective factors are those that can be translated into monetary terms such as labour, transportation, and raw material costs. Subjective factors are those with qualitative measures. For example, the attitude of a community towards a factory project, which cannot be quantified in monetary terms, is considered as a subjective factor. It should be noted that a factor can be classified as both subjective and critical.

The model integrates the three categories of factors presented above and expresses the location measure LM_i for each site i. LM_i is a combination of three terms: (1) critical factor measure (CFM_i), (2) objective factor measure (OFM_i), and (3) subjective factor measure (SFM_i). It is defined as follows [46]:

$$LM_i = CFM_i[\alpha \times OFM_i + (1-\alpha) \times SFM_i],\ i = 1, 2, \ldots,\ m, \tag{1}$$

where

$$CFM_i = \prod_j CFI_{ij},\ i = 1,\ 2, \ldots,\ m, \tag{2}$$

where CFI_{ij}, the critical factor index for location i with respect to the critical factor CF_j, takes the value 1 if location i meets the requirement of the critical factor CF_j, and 0 otherwise. This means that for any site i which do not meet the requirement of a critical factor CF_j, the critical factor index CFI_{ij}, and hence CFM_i (Equation (2)) and LM_i (Equation (1)) take the value 0. In this case, the site is excluded from the ranking even if it meets the requirements for other critical factors.

$$OFM_i = \frac{max_i\left[\sum_{j=1}^{q} OF_{ij}\right] - \sum_{j=1}^{q} OF_{ij}}{max_i\left[\sum_{j=1}^{q} OF_{ij}\right] - min_i\left[\sum_{j=1}^{q} OF_{ij}\right]},\ i = 1,\ 2, \ldots, m, \tag{3}$$

where $\sum_{j=1}^{q} OF_{ij}$ represent the sum of all objective factors related to setting the plant at location i. The model requires that the objective factors be cost-based and consider any inflow-based factor by placing a negative sign in front of it. The site with the maximum $\sum_{j=1}^{q} OF_{ij}$ obtains an OFM_i value of zero, while the one with the smallest $\sum_{j=1}^{q} OF_{ij}$ value obtains an OFM_i value of one.

$$SFM_i = \sum_{j=1}^{r} w_j SF_{ij},\ i = 1,\ 2, \ldots\ldots, m, \tag{4}$$

where SF_{ij} (j = 1, ..., r) is the value on the 0–1 scale of the subjective factor j at site i. w_i is the weight assigned to the subjective factor j ($0 \le w_j \le 1$ and $\sum_{j=1}^{r} w_i = 1$).

- α is the objective factor decision weight. It should be between 0 and 1.
- The best location for setting the plant is the one with the highest location measure (LM).

2.4.2. Modified Brown–Gibson Model for Utility-Scale PV Plants

- Net Present Value (NPV)

The original model of Brown–Gibson has the disadvantage of not taking into account the time value of money (TVM) when accounting for the costs and revenues of a project at a given location. This makes the application of the original model impossible for a utility-scale solar PV project since the corresponding cash flows are spread over the life of the project and include investment costs, operating and maintenance costs, inverter replacement costs, and revenues from the sale of electricity produced. Taking into account the TVM by discounting all objective factors (cash flows) associated with the project at location i led the replacement of the sum of objective factors in the original model by the opposite of the NPV:

$$\sum_{j=1}^{q} OF_{ij} = -\sum_{i=0}^{T} \frac{NCF_{it}}{(1+r)^t} = -NPV_i, \quad (5)$$

where NPV_i is the NPV of the hypothetical PV project at location i, and NCF_{it} the net cash flow of the project in location i in year t. T represents the project lifetime, and r is the discount rate. The NPV_i was determined using RETScreen software, as explained in Section 2.3. The negative sign was added to reflect the fact that objective factors are cost-based in the model, as explained in the previous sub-section. Further information about the NPV of utility-scale photovoltaic plants can be found in [17–22]. Therefore, in light of the above, OFM_i, the objective factor measure for location i was expressed as follows:

$$OFM_i = \frac{NPV_i - min_i[NPV_i]}{max_i[NPV_i] - min_i[NPV_i]}, \ i = 1, 2, \ldots, m, \quad (6)$$

Hence, the ranking of the alternative sites based on the NPV of the proposed PV system is equivalent to that based on the objective factor measure of the sites. The locations with the maximum and minimum NPVs will then receive an objective factor measure of 1 and 0, respectively.

- Critical factors

In addition to four constraint factors selected based on the studies carried out in [27–31], the constraints related to the NPV and SPP of the solar PV project were considered. As a rule, a project is accepted if its NPV is higher than 0. Besides, the common acceptable maximum SPP for commercial PV projects is eight years [47]. Due to risks associated with the first implementation of such a project in Cameroon, a maximum acceptable SPP of 6 years was considered. Thus, the following elements were considered as critical factors:

1. CF_1: Buffer of residential areas = 1000 m
2. CF_2: Buffer of waterway = 500 m
3. CF_3: Buffer of protected areas = 500 m
4. CF_4: Buffer of wildlife = 1000 m
5. CF_5: NPV constraint (NPV ≥ 0€) (From RETScreen)
6. CF_6: SPP constraint (SPP ≤ 6 years) (From RETScreen)

- Suitability factors

Seven suitability factors were used instead of the subjective factors of the original model. Those criteria were selected from the evaluation criteria of utility-scale PV plants used in [27–31]. Those already considered in RETScreen simulation like solar radiation were not selected. On the other hand, the average temperature and average wind speed which affect the performance of photovoltaic systems [48] and are not considered in the RETScreen simulation were selected. The selected suitability factors are as follows:

1. SF1: Distance from residential areas
2. SF2: Land use (= 1 for forest, 2 for cultivated land, 3 for pasture, and 4 for bare land/desert)
3. SF3: Distance from road
4. SF4: Distance from the power grid
5. SF5: Carbon emission saving (From RETScreen)
6. SF6: Annual average temperature
7. SF7: Annual average wind speed

These seven factors were classified in three categories, namely, environmental, climatic, and location. A hierarchy representation of the selected suitability criteria is represented in Figure 6.

- Considering the selected criteria above and the Equations (1), (2), (4) and (6), the following location model for utility-scale photovoltaic systems was obtained:

$$LM_i = \prod_{j=1}^{5} CFI_{ij} \left[\propto \frac{NPV_i - min_i[NPV_i]}{max_i[NPV_i] - min_i[NPV_i]} + (1 - \propto) \sum_{j=1}^{7} w_j SF_{ij} \right], \ i = 1, 2, \ldots, m \tag{7}$$

where

LM_i = location measure of site i,
CFI_{ij} = critical factor index of the critical factor CF_j at location i,
SF_{ij} = 0–1 scale, normalized value of the suitability factor SF_j at location i,
NPV_i = Net present value of the PV project at location i,

- α = the objective factor decision weight. The value of α for this study was 0.6.
- The normalized values SF_{ij} were obtained from the values of suitability factors $\overline{SF}_{ij}$ using the following normalization formulas [49]:

$$SF_{ij} = \frac{\overline{SF}_{ij} - min_y \overline{SF}_{yj}}{max_y \overline{SF}_{yj} - min_y \overline{SF}_{yj}}, \tag{8}$$

for criteria of maximum,

$$SF_{ij} = \frac{max_y \overline{SF}_{yj} - \overline{SF}_{ij}}{max_y \overline{SF}_{yj} - min_y \overline{SF}_{yj}}, \tag{9}$$

for criteria of minimum.

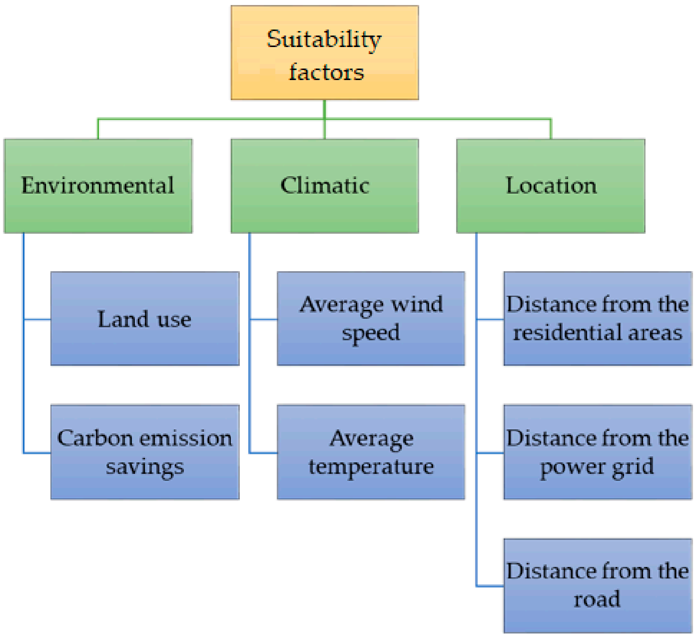

Figure 6. The hierarchy representation of suitability factors.

Based on previous studies [27–31], the average yearly temperature (AYT), distance from the power grid (DPG) and distance from the road (DR) were considered as criteria of minimum, while the average yearly wind speed (AYWS), carbon emission saving, distance from residential areas (DRA), and land use (LU) were considered as criteria of maximum.

- The suitability factor weights were determined using the Analytic Hierarchy Process (AHP). The details about the calculation are given in the next section.
- The coefficient of variation (CV) was used to compare the LM and NPV parameters in site differentiation. The CV is the ratio of the standard deviation to the mean [50].

2.5. AHP (Analytic Hierarchy Process)

The Analytic Hierarchy Process (AHP) approach was used to calculate the weighting of the suitability factors in this study. Initially developed by Thomas Saaty in the 1970s, it is one of the most widely used MCDM methods. It has previously been used in [27–31] for calculating the weight of criteria in site selection for utility-scale solar PV projects.

The AHP method is based on pairwise comparisons leading to the building of decision matrices (pairwise comparison matrices) at each level of the hierarchical structure of the criteria. The values used for the comparison in pairs are integers between 1 and 9 or their reciprocal. The vector $w = [w_1, w_2 \ldots w_n]$, whose elements are the weighting factor, is retrieved from the pairwise comparison matrix A using the following two-step procedure:

1. Divide each entry of column i by the sum of entries in column i to form A_{norm}
2. Obtain w_i as the mean of the entries in row i of A_{norm}.

Besides, the consistency ratio (CR) is used to eliminate inconsistent judgments of decisions in the comparison process:

$$CR = \frac{Consistency\ Index\ (CI)}{Random\ Index\ (RI)} \tag{10}$$

where

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{11}$$

where λ_{max} is the maximum Eigen value of the matrix A and n its size. The RI for different value of n are shown in Table 5.

Table 5. Random Index table [51].

n	2	3	4	5	6	7	8	9	10	11	12
RI	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48

If CR ≤ 0.1, the degree of consistency is considered satisfactory. The weighting factors calculated by the AHP can only vary according to the pairwise comparison matrix, based on the judgments of the decision-maker. Further information about the AHP method is available in [51].

For this study, four pairwise comparison matrices were constructed according to the hierarchical structure of suitability factors, as shown in Figure 7. These matrices are presented in Tables 6–9. All four related values of the consistency ratio were less than 0.1, meaning that value judgments were acceptable.

Table 6. Comparison matrix of suitability factor categories.

	Environment	Climatic	Location
Environment	1	2	1
Climatic	1/2	1	1/3
Location	1	3	1

Table 7. Comparison matrix of environmental factors.

	Land Use	Carbone Emission
Land use	1	2
Carbone emission	1/2	1

Table 8. Comparison matrix of climatic factors.

	Average Wind Speed	Average Temperature
Average wind speed	1	2
Average temperature	1/2	1

Table 9. Comparison matrix of the criteria location factors.

	DRA	DPG	DR
DRA	1	2	1
DPG	1/2	1	1/3
DR	1	3	1

DRA: distance from residential areas; DR: distance from the road; DPG: distance from the power grid.

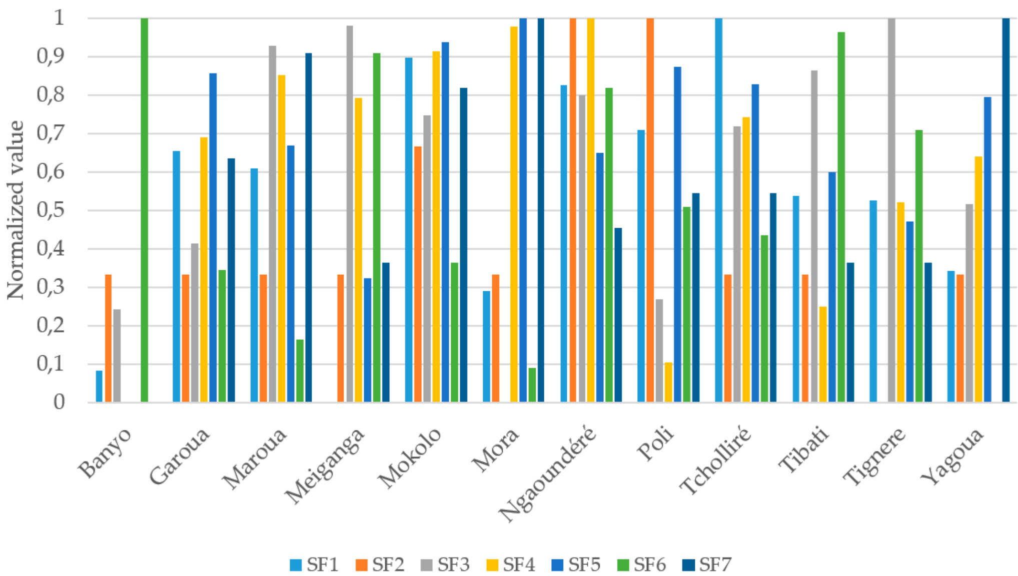

Figure 7. Normalized values of the suitability factors at each site.

2.6. Sensitivity Analysis

Sensitivity analysis is the technique applied to evaluate how the change in specific parameters impact the outputs or performance of the system. It can be applied to explore the robustness and accuracy of the model results under uncertain conditions. In this study, the sensitivity of the location measures of different site alternatives to change in the objective factor coefficient (α) was investigated.

3. Results and Discussion

Table 10 displays the results of RETScreen simulation of the proposed PV plant at each site. The project's NPV ranges from €1.515 million in Banyo to €2.342 million in Mora, with a mean of €2.066 million, a standard deviation of €0.237 million, and a coefficient of variation of 11.5%. If the NPV were considered as the only criterion of evaluation, Mora would be the best site, followed by Mokolo and Poli. The electricity fed into the grid, the reduction of greenhouse gas emissions, and the capacity factor of the PV system all vary from Banyo to Mora, from 10,671 MWh/year to 11,567 MWh/year, from 9156 tCO_2/year to 9797 tCO_2/year, and from 24.4% to 26.1%, respectively. All sites meet the NPV constraint (NPV ≥ 0€). Only the Banyo and Meiganga sites do not comply with the SPP constraint (SPP ≤ 6 years).

Table 10. RETScreen simulation results.

Location	CF (%)	EG (MWh/y)	GHG E.R. (tCO_2/y)	NPV (M€)	SPP (Years)
Banyo	24.4	10,671	9156	1.515	6.3
Garoua	25.8	11,311	9705	2.224	5.9
Maroua	25.5	11,172	9585	2.069	6
Meiganga	24.9	10,914	9364	1.784	6.1
Mokolo	26.0	11,372	9757	2.291	5.9
Mora	26.1	11,419	9797	2.342	5.9
Ngaoundéré	25.5	11,167	9572	2.052	6
Poli	25.9	11,324	9716	2.237	5.9
Tchollіré	25.8	11,291	9687	2.201	5.9
Tibati	25.4	11,119	9540	2.011	6
Tignere	25.2	11,024	9458	1.905	6
Yagoua	25.7	11,266	9666	2.163	5.9

CF: capacity factor; EG: electricity to the grid; GHG E.R.: greenhouse gas emission reduction; NPV: net present value; SPP: simple payback period.

The results of the calculation of the normalized values of the seven suitability factors for each site according to formula (8) or (9) are plotted in Figure 7, while the results of weighting calculation of these seven factors using the AHP approach are presented in Table 11. The critical factor indices for each site against each critical factor are shown in Table 12.

Table 11. Weight of criteria and factors.

Criteria	Suitability Factor	Weight of Factor (%)
Environmental (38.7%)	Land use (SF_2) (66.7%)	25.8
	Carbone emission saving (SF_5) (33.3%)	12.9
Climatic (16.9%)	Average wind speed (SF_7) (50%)	8.45
	Average temperature (SF_6) (50%)	8.45
Location (44.4%)	Distance from residential areas (SF_1) (24.0%)	10.7
	Distance from power grid (SF_4) (55%)	24.4
	Distance from the road (SF_3) (21%)	9.3

Table 12. The critical factor indices for each location.

Location	CFI_1	CFI_2	CFI_3	CFI_4	CFI_5	CFI_6
Banyo	0	1	1	1	1	0
Garoua	1	1	1	1	1	1
Maroua	1	1	1	1	1	1
Meiganga	0	1	1	1	1	0
Mokolo	1	1	1	1	1	1
Mora	1	1	1	1	1	1
Ngaoundéré	1	1	1	1	1	1
Poli	1	0	1	1	1	1
Tchollіré	1	1	1	1	1	1
Tibati	1	1	1	1	1	1
Tignere	1	1	1	1	1	1
Yagoua	1	1	1	1	1	1

With reference to the previous results, the critical factor measure (CFM), objective factor measure (OFM), suitability factor measure (SFM) for each site were calculated based on formulas (2), (4) and (6) respectively. The results, plotted in Figure 8, show that Ngaoundéré has the highest suitability factor measure, while Mora has the highest objective factor measure. The results of the calculation of the location measure (LM) (based on the formula (7)) and the ranking of alternative sites according to the Brown–Gibson model are presented in Table 13. The Banyo, Meiganga and Poli sites that have a zero critical factor measure and a consequent location measure of zero are excluded from the ranking. The site of Mokolo that received the highest value of the LM (0.88) is the optimal location for the proposed solar photovoltaic system, followed by Mora (0.83) and Tchollíré (0.75). The mean, standard deviation, and coefficient of variation of the location measure of the selected locations are respectively 0.52, 0.33, and 63%.

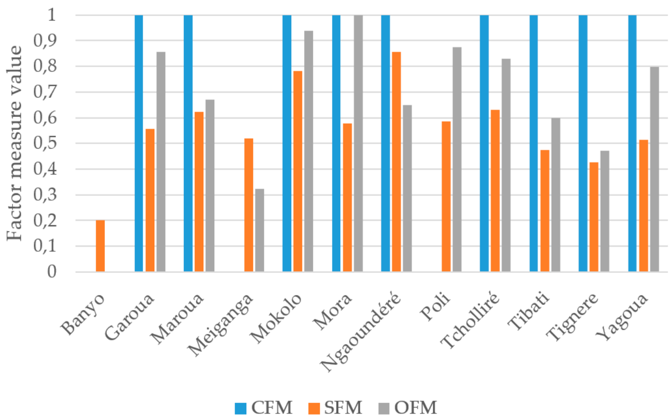

Figure 8. Factor measures (critical factor measure (CFM), suitability factor measure (SFM), & objective factor measure (OFM)) of each location.

Table 13. Location measures and ranking of alternative sites.

Location	LM	Rank
Banyo	0	Not ranked
Garoua	0.74	4
Maroua	0.65	7
Meiganga	0	Not ranked
Mokolo	0.88	1
Mora	0.83	2
Ngaoundéré	0.73	5
Poli	0	Not ranked
Tchollíré	0.75	3
Tibati	0.55	8
Tignere	0.45	9
Yagoua	0.68	6

These results show that location measure has a coefficient of variation much higher than that of the NPV calculated by RETScreen, meaning that it allows for better differentiation of the alternative sites.

Figure 9 shows the results of the sensitivity analysis of location measures with respect to objective factor coefficient (α). Regardless of the objective factor coefficient, the location measure of the Banyo, Meiganga, and Poli sites is null because of the nullity of their critical factor measure. If only suitability factors were to be considered, that is, $\alpha = 0$, Ngaoundéré will be the most preferred site. The latter will remain the best site for values of α less than 0.2. Mokolo becomes the best location if the objective factor coefficient lies between 0.2 and 0.78, while Mora is the best site for values of α higher than 0.78. These results more clearly bring out the optimality of the Mokolo site since the appropriate value of α belongs to the interval [0.3–0.7] [52].

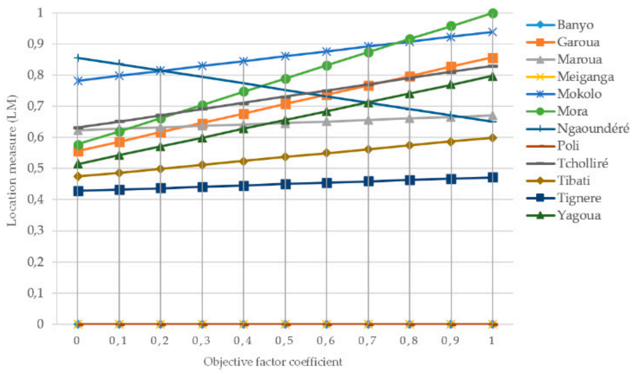

Figure 9. Sensitivity analysis of location measure for each site with respect to objective factor coefficient.

One of the innovative aspects of this study is the consideration of the time value of money (TVM) in the Brown–Gibson model. This made the model more consistent for optimal location of utility-scale solar PV systems and led to the introduction of the NPV parameter of the system, which was combined with the criteria considered in [27–31] in a single framework analysis. The proposed model is thus superior to that applied in [25–30] which ranks alternative sites solely according to the NPV of a hypothetical solar PV system. The developed model can easily adapt if critical factors or suitability factors are added or deleted from those considered in this analysis to take into account different requirements or evaluation systems of different stakeholder groups involved in a particular case. Those stakeholders may include, among others, institutions and administrative authorities such as communities and local authorities, environmental groups, potential investors, and governments.

This study thus contributes to enriching the literature in decision-making processes for renewable energy development. Selecting appropriate sites constitutes a critical step towards developing feasible renewable energy projects. This is all the more important as 179 countries around the world have set a renewable energy target and taken steps to accelerate their deployment. As far as 2017, 57 countries have developed plans for the complete decarbonization of their electricity sector [5].

Additional research will be required to address the limitations of this study, including (1) the non-consideration of the public acceptance in the site selection process, (2) the failure to undertake the sensitivity analysis of optimal location with respect to the PV module type and the size of the installation, and (3) the failure to investigate other parameters such as debt term and capital cost subsidy that may impact the viability of photovoltaic systems.

4. Conclusions

This study proposed a multi-criteria decision-making approach based on the Brown–Gibson model for optimal location of utility-scale solar photovoltaic plants. Applied in northern Cameroon, the method designed made it possible to rank a set of twelve alternative sites for a 5 MW solar photovoltaic project, considering the requirements and evaluation systems of the various actors who may be involved in the project. The development of this method constitutes an essential contribution to the renewable energy sector as it will help decision-makers to make more consistent and robust decisions in renewable energy planning, especially as the development of renewable energies is of paramount importance in most countries around the world. In the context of Cameroon, such a development could help to provide new impetus in solving the current energy crisis, especially since the government has set out in Cameroon Vision 2035 its ambition to make the country an emerging economy by 2035.

Author Contributions: Conceptualization, N.Y.; methodology, N.Y. and M.D.; validation, M.D.; formal analysis, N.Y.; investigation, N.Y.; writing—original draft preparation, N.Y.; writing—review and editing, M.D.; supervision, M.D.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. List of acronyms used in the paper.

Acronyms	Meaning
AC	Alternating Current
ADSR	Average Daily Solar Radiation
AHP	Analytic Hierarchy Process
AYT	Average Yearly Temperature
AYWS	Average Yearly Wind Speed
BCR	Benefit-Cost Ratio
CF	Critical Factor
CFI	Critical Factor Index
CFM	Critical Factor Measure
CI	Consistency index
CR	Consistency Ratio
DC	Direct Current
DPA	Distance from Protected Areas
DPG	Distance from the Power Grid
DR	Distance from the Road
DAR	Distance from Residential Areas
DWL	Distance from Wildlife
GHGs	Greenhouse Gases
GSR	Global Solar Radiation Levels
IEA	International Energy Agency
IRR	Internal Rate of Return
LM	Location Measure
LU	Land Use
MCDM	Multi-Criteria Decision-Making
NIG	Northern Interconnected Grid
NREL	US National Renewable Energy Laboratory
OF	Objective Factor
PV	Photovoltaic
RI	Random Index
RESs	Renewable Energy Sources
RETs	Renewable Energy Technologies
SF	Suitability Factor
SFM	Suitability Factor Measure
SPP	Simple Payback Period
SSE	Surface meteorology and Solar Energy
TVM	Time Value of Money

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