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Onshore Wind Farms Suitability Analysis Using GIS-based AHP-PROMETHEE II

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Abstract

Wind energy is the most abundant, mature, and wide range of all renewable energy, and its optimal use results in enhanced energy security and affordability. However, wind farm suitability analysis is a crucial decision-making process that involves various stakeholders with different biases and concerns. Thus, effective planning of limited land resources and utilization of renewables ensure low environmental impact, high economic gains, and minimal community disturbances. This study presents a GIS-based AHP-PROMETHEE II framework that addresses the need for efficient onshore wind farms suitability analysis. The framework is illustrated through a case study in Cagayan Province. The results showed that there are 10.16% unsuitable, 47.45% least suitable, and 6.08% most suitable areas in the study area. The results also showed that the least suitable areas are inland while the most suitable areas are near coastal areas as validated by the sole wind energy service contract in the study area. In addition, the AHP's underlying value judgments, inconsistencies, and limitations can be addressed by PROMETHEE II. The proposed framework can be used as a more strategic planning tool by decision-makers for onshore wind farm siting developments and can be a guide for regional or national scale mapping.

1. Introduction

The optimal use of renewable energy is necessary in reducing greenhouse gas emissions and attaining sustainable development.. The shortage of non-renewable sources for energy consumption forced energy sectors to find alternatives worldwide (IPCC, 1990; UNFCC, 1992). Despite numerous efforts to develop sustainable use of energy, developing countries such as the Philippines fail to achieve their energy agenda.

Of all renewable energy, wind resources are deemed to be the most abundant, cost-effective, mature, and wide range (Xu, et al., 2020). However, there are negative impacts that may hinder rapid wind energy development. These impacts can alter the normal life of residents and the natural environment; therefore, it is of highest viability to do scientific research and suitability analysis to achieve the highest potential of any renewable energy projects. In the context of the Philippines, it has an excellent wind energy potential, especially in the northern areas, with a total of 11,055 square kilometer of windy territory that has a maximum generation capacity of 76,000 MW and which is theoretically suitable to connect to the main energy grid (IRENA, 2017).

The site selection process is a spatially complex decision-making problem that needs careful considerations of environmental and planning constraints (Sotiropoulou & Vavatsikos, 2021). With the use of various multi-criteria decision analysis (MCDA) methods, the conflicting problems, advantages and disadvantages, risks, and benefits can be handled scientifically. Hence, GIS is combined with MCDA techniques to solve decision-making problems involving conflicting and/or multiple criteria. The synthesis of GIS tools and MCDA techniques enhance the effectiveness of wind farm site selections (Rikalovic, et al., 2014).

In recent years, various studies involving GIS and weight-based MCDA techniques have been developed to effectively conduct site-selection processes. The problem with these techniques, such as Analytical Hierarchy Process (AHP), is that there are uncertainties that cannot be fixed using values and fail to describe the characteristics of each criterion (Xu, et. al, 2020).

This study synergizes the use of AHP and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) II framework in onshore wind farms suitability analysis. This framework can be utilized as a tool for wind energy developers to determine the most suitable site for wind farm developments. This study is also aligned with the Sustainable Development Goals initiative of the United Nations specifically contributing to achieving SDG 7, which is ensuring affordable and clean energy for all. In view of this, the method is validated by comparing its results with the existing data of onshore wind farms in the Philippines. This study also analyzes the generated AHP and PROMETHEE II suitability maps.

2. Methodology

2.1 Study Area

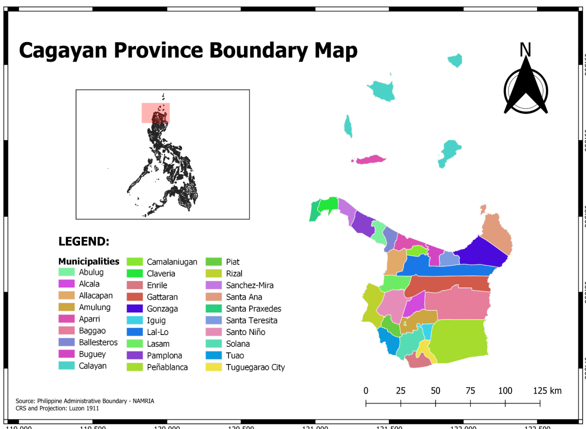

Figure 1. Boundary map of Cagayan Province.

The suitability analysis focuses on the Cagayan Province in the Philippines. The study area is approximately 9,398 square kilometers, with a population of approximately 1.3 million inhabitants, according to the 2020 Census of Population and Housing. The electricity supply in the area is often interrupted and costly due to its location. Currently, the power supply of Cagayan Province is mainly sourced from coal-fired power plants in Bataan which is costly to transmit. The Philippine Renewable Energy Atlas 2017 categorizes the Cagayan Valley region, where the Cagayan province is located, to have the highest wind energy generating potential. However, in 2017, there are only 10 renewable energy projects in the study area composed of offshore wind farms, solar power plants, and biomass power plants (DOE, 2017). The map of the extents and municipalities of Cagayan province is shown in Figure 1.

2.2 Data Requirements

GIS-based suitability analysis uses attributes to provide a scale of measuring the candidate locations based on decision criteria. Attributes are evaluation criteria (such as constraints and factors) that can be ascending or descending depending on their contribution to site selection decision-making (Latinopoulos and Kechagia, 2015). In this study, fourteen constraints and criteria will be used. These sets of considerations are adopted from the Project 5: *Philippine Renewable Energy Resource Mapping from LiDAR Surveys (REMap)* under Phil-LiDAR 2 Program, ensuring consistency with the AHP weights used in the PROMETHEE II method, which were also derived from the same program. The pixel dimensions to be used are 30 by 30 m which was patterned with the resolution of the ASTER GDEM dataset from which the surface roughness criteria were extracted. The summary of attributes, constraints, and factors is shown in Figure 2 while criteria type, threshold, and justification are shown in Table 1.

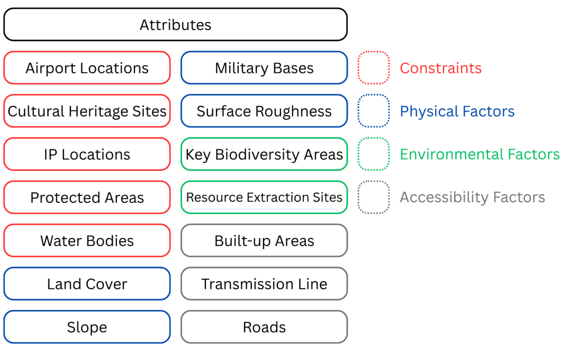

Figure 2. Constraints and factors for wind farm siting.

Attributes	Type	Buffer Zone	Justification
Airport Locations	p	1 km	To assure safety in aviation facilities due to possible turbine interference with aviation radio signals and to maintain visibility (van Haaren and Fthenakis, 2011).
Cultural Heritage Sites	p	1 km	To preserve the cultural heritage areas including archaeological sites, cultural monuments, and historical sites (Tsoutsos et al, 2015).
IP Locations	p	None	To preserve the ancestral lands, it is ethical to consider the Indigenous Peoples (IP) locations due to their close relationship with the environment (Shah and Bloomer, 2018).
Protected Areas	p	0.5 km	To protect the habitats of animals and endangered species plants, and to preserve nature reserves, wetlands and national parks (Aydin et al., 2010).
Water Bodies	p	0.4 km	Water bodies such as lakes and rivers pose flooding related hazards on wind farms. To eliminate the costs of maintenance, wind farms should not be within 400 m of water bodies (Baban and Parry, 2001; Aydin et al., 2010).
Land Cover	p	None	The type of land that is used for wind farm developments directly affects its productivity and power generation (Maguire et al., 2024).
Slope	q	None	Higher installation and maintenance costs are influenced by steep slopes which limit the accessibility to construction and are prone to turbulence (Baban and Parry, 2001).
Military Bases	p	1 km	Army grounds such as military bases are infeasible for wind farm installation (van Haaren and Fthenakis, 2011).
Surface Roughness	q	None	Surface roughness refers to deviations from the normal vector of a real surface This means that the highest mean wind speed occurs in areas with low surface roughness (Jung and Schindler, 2020).
Key Biodiversity	p	0.5 km	To protect and promote the environment, key

Areas			biodiversity areas must be included as a consideration. For example, birds near wind energy facilities often encounter direct or lethal impacts from collisions to the wind turbines and associated infrastructure (Hein et al., 2012).
Resource Extraction Sites	p	0.5 km	To avoid potential conflicts from other pre-established investments, the planning phase should include distance from industrial areas and mining zones (Baseer et al., 2017).
Built-up Areas	p	0.5-0.8 km	To safeguard urban areas from visual intrusion, noise pollution, and shadow flicker effects due to wind turbines, an appropriate minimum distance from urban areas must be implemented (Baban and Parry, 2001; Baseer et al., 2017)
Distance from Transmission Line	q	15 km	To avoid transmission losses, operational costs, and high cabling, wind farms should be located within the nearest electricity grid (Sotiropoulou and Vavatsikos, 2021).
Distance from Roads	q	3.2 km	For accessibility purposes, the nearer the wind farm site to the road network is recommended; hence, the greater the preference (Tegou et al., 2010).

Table 1. Summary of attributes, type (where p = ascending and q = descending), buffer zone, and justification.

2.3 GIS-based AHP-PROMETHEE II

The process flow chart of the methodological framework is illustrated in Figure 3. In generating the suitability map, two processes are involved: absolute and relative suitability analysis. Absolute suitability refers to the classification of possible sites based on criteria that determine whether a location is suitable or not. It involves assessing locations based on constraints that inherently meet the technical, environmental, and regulatory requirements needed in the area. In addition, the possible locations are assumed to be independent of each other to only assess if they are suitable or unsuitable. In this study, as shown in Figure 2, the constraints are airport locations, cultural heritage sites, IP locations, protected areas, and water bodies.

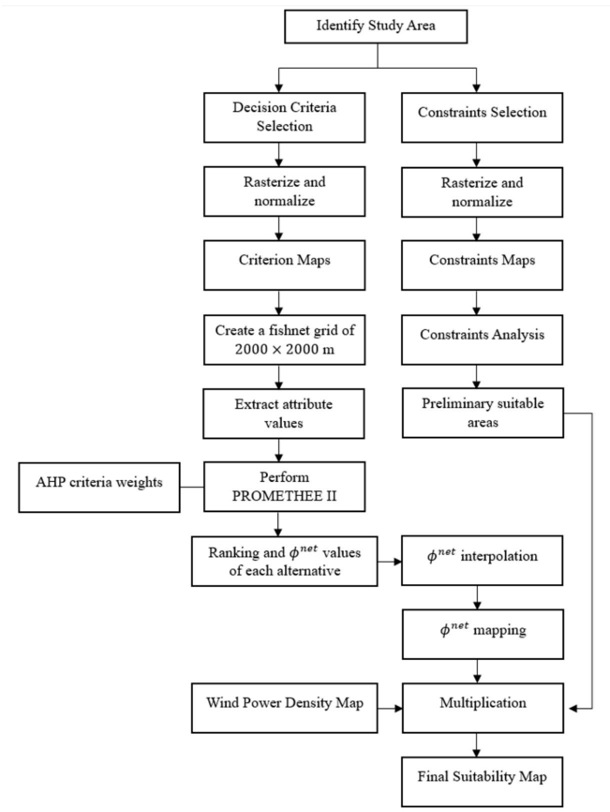

Figure 3. GIS-based AHP-PROMETHEE II framework.

On the other hand, relative suitability refers to comparing multiple sites against each other by ranking them on how well they meet the criteria set. It is an approach that identifies the best alternatives by using MCDA methods. Unlike absolute suitability that classifies sites based on constraints, relative suitability ranks possible locations based on their likeability and conformity to the factors set. In this study, as shown in Figure 2, the factors are divided into three groups with respect to physical (land cover, slope, military bases, and surface roughness), environmental (key biodiversity areas and resource extraction sites), and accessibility (built-up areas, transmission line, and roads). In generating the final suitability map, the results of the absolute and relative suitability maps are equally overlaid to reflect the areas that are not suitable, less suitable, moderately suitable, suitable, and most suitable.

Referring to relative suitability analysis, the MCDA methods used in this study are AHP and PROMETHEE II. AHP is an MCDA technique that ranks alternatives based on concurrent evaluation of all decision criteria through pairwise comparison of the relative importance of two criteria (Saaty, 1977). Selected stakeholders and decision makers will compare the relative importance of each criterion to one another, and these pairs are stored in reciprocal ratio matrices that are measured using 1-9 scale measurement to show the intensity of preferences, thus a pairwise comparison matrix is created. The relative weights on reciprocal ratio matrices are normalized through dividing each pairwise weight to the sum of pairwise weights on the column it belongs to (Malczewski, 1999). The average of each row of the normalized matrix is the vector of weights (w). This approach, also known as the Approximate Eigenvector method, can be expressed as:

$$Aw = \lambda_{max} w \tag{1}$$

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where Aw = pairwise comparison matrix
λ_{max} = principal eigenvalue
w = vector weights

AHP is a mathematical tool that helps with decision-making since its process involves identifying the problem, determining goal, and ranking criteria that are needed in obtaining objectives to solve the given problem. In onshore wind farm siting, AHP is also widely used for assigning weights on decision criteria, whether it is a stand-alone method or integrated on other MCDA techniques (Tegou and Polatidis, 2010; Baseer, et al., 2017). In the context of the study area, AHP has also been used for various renewable energy applications in the Philippines (Galvan, 2021; Sotto et al., 2023). In this study, the AHP weights are adopted from the Project 5: *Philippine Renewable Energy Resource Mapping from LiDAR Surveys (REMap)* under Phil-LiDAR 2 Program, as shown in Table 1. The program conducted two workshops to get the perspectives of different agencies and stakeholders when developing wind energy power plants in the Philippines (Ang and Blanco, 2017). The first workshop focused on criteria determination while the second workshop focused on AHP weights determination. The survey participants were clustered into four composed of academe, developers, environmentalists, and policymakers.

Criteria	AHP Weights
Key Biodiversity Areas	0.208496
Transmission Lines	0.176614
Roads	0.164498
Built-up areas	0.124888
Resource Extraction Sites	0.123504
Military Bases	0.060802
Slope	0.058984
Surface Roughness	0.046258
Land Cover	0.035956

Table 2. AHP weights adopted from Phil-LiDAR 2 program.

PROMETHEE II is from a family of multi-attribute decision making analysis approaches that outranks criteria aside from weights (Brans and Mareschal, 2005). Its implementation starts with the determination of weights where the decision-maker can utilize other MCDA methods to identify the weights of each criterion. In this study, the AHP weights in Table 2 were used. Next, for each criterion a preference function is generated. Preference functions are the difference between two alternatives into a preference degree ranging from zero to one (Vincke and Brans, 1985). The determination of deviations based on pairwise comparisons denotes the difference between evaluations of a and b on each criterion, as expressed in:

$$d_j(a,b) = g_j(a) - g_j(b) \tag{2}$$

where $d_j(a,b)$ = difference between two alternatives
$g_j(a)$ = evaluation score of alternative a on criteria j
$g_j(b)$ = evaluation score of alternative b on criteria j

To denote the preference of alternative a with alternative b on each criterion as a function, a preference function can be expressed as:

$$P_j(a,b) = F_j[d_j(a,b)] \tag{3}$$

where $P_j(a,b)$ = preference degree between 0 and 1
F_j = preference function associated with criterion j
$d_j(a,b)$ = difference between two alternatives

Preference values can be set as minimum (non-beneficial criteria) or maximum (beneficial criteria) depending on the decision makers' preferences. The preference functions are also set based on the six preference functions with different applications such as usual, linear, quasi, level, V-shape, and gaussian (Behzadian et al., 2010). After this, the global preference index which is the weighted sum for each criterion is calculated, as given in the equation below:

$$\pi(a,b) = \sum_{j=1}^{k} w_j P_j(a,b) \tag{4}$$

where $\pi(a,b)$ = overall preference of alternative a over b
k = number of criteria
w_j = weight assigned to criterion j
$P_j(a,b)$ = preference degree between 0 and 1

After this, the outranking flows are calculated to get the positive and negative outranking flow for each alternative, the equations are expressed as:

$$\phi^{+} = \frac{1}{n-1} \sum_{a,b \in A} \pi(a,b) \tag{5}$$

$$\phi^{-} = \frac{1}{n-1} \sum_{a,b \in A} \pi(a,b) \tag{6}$$

where ϕ^{+} = positive outranking flow
ϕ^{-} = negative outranking flow
n = total number of alternatives
$\pi(a,b)$ = overall preference of alternative a over b

The concept of outranking flows are used to rank and evaluate each alternative. $\phi+$ values show how an alternative is preferred over the others. The higher the $\phi+$ value, the more liked an alternative is. Conversely, $\phi-$ values represent how weak or outranked an alternative to other alternatives. To get the net outranking flows for each alternative, the difference between the positive and negative outranking flows is calculated, as expressed in:

$$\phi^{net}(a) = \phi^{+}(a) - \phi^{-}(a) \tag{7}$$

where ϕ^{net} = net outranking flow of alternative a
$\phi^{+}(a)$ = positive outranking flow of alternative a
$\phi^{-}(a)$ = positive outranking flow of alternative a

The net flow of preferences is derived from net outranking flow values. These values provide a measure on the overall preference or dominance of an alternative with other alternatives. This implies that the number one ranked alternative is the most preferred alternative out of all the others. On the contrary, the lowest ranked alternative is the least preferred alternative. The use of PROMETHEE II method in onshore wind farm site selection is uncommon in that only two known studies have been identified (Ghobadi and Ahmadipari, 2018; Sotiropoulou and Vavatsikos, 2021).

3. Results and Discussion

3.1 Absolute Suitability

To generate the final suitability map, a constraints map is needed to fulfill its requirements. The unsuitable areas on the map are constraints such as airport locations, cultural heritage sites, IPs locations, protected areas, and waterbodies. The constraints coverage is approximately 10.16% of the study area. This means that there are around 89.84% preliminary suitable areas left where the decision criteria and MCDA methods could be implemented.

3.2 Relative Suitability

The process of integrating GIS and MCDA methods such as PROMETHEE II refers to relative suitability. The application of PROMETHEE II, as illustrated in Section 1, resulted in an estimation per alternative. This means that every point (alternative) in the generated fishnet could be ranked based on their overall suitability level. The PROMETHEE II ϕnet map was reclassified to 25% equal interval to get its distinct categories that are based on equal intervals (Sotiropoulou et al., 2023). The normalized PROMETHEE II ϕnet map is shown in Figure 4.

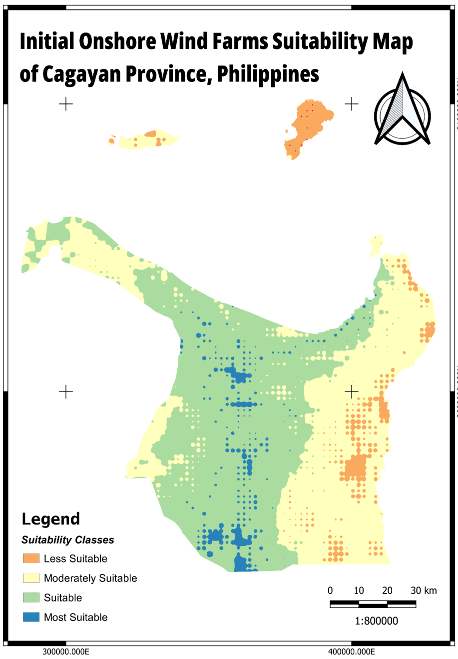

Figure 4. Normalized PROMETHEE II ϕnet map.

The relative suitability analysis shows that after PROMETHEE II implementation, there are around 2.80% most suitable and 51.45% suitable areas for onshore wind farms installation in Cagayan province. On the other hand, there are around 40.79% moderately suitable and 4.97% least suitable areas. Based on Figure 3, the most suitable areas are within the municipalities of Enrile, Solana, Alcala, Camalaniugan, and Aparri. These municipalities are the nearest to the transmission line and road network. Meanwhile, the least and moderately suitable areas are on the northernmost left side within the municipalities of Claveria, Sanchez, and Pamplona, the northern islands, and on the right side of Cagayan Province where the Sierra Madre mountain ranges are located. These results are obtained because these areas are in high slopes and with rough terrains, especially in the Sierra Madre mountain ranges and the municipalities near it, make it least suitable for onshore wind farm development.

3.3 Final Suitability Map

In generating the final suitability map, a 100 m WPD map from Phil-LiDAR 2 Program was overlaid equally to the absolute and relative suitability maps. To generate the final suitability map, WPD, absolute, and relative suitability maps are overlaid into a single map. The map is shown in Figure 5.

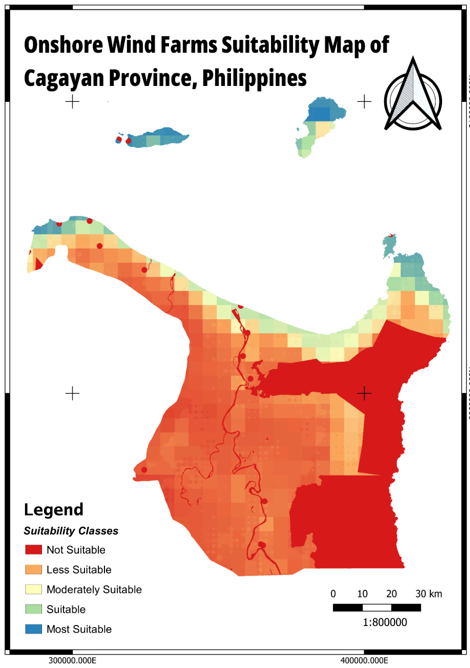

Figure 5. Final Suitability Map.

Based on the final suitability map, there are 10.16% unsuitable, 47.45% least suitable, 26.73% moderately suitable, 9.58% suitable, and 6.08% most suitable areas in Cagayan province. These suitability results that are classified based on considerations shown in Figure 2 can be used as a basis for scenario-based planning. For instance, if a project prioritizes maximum energy output, decision-makers should prioritize "most suitable" and "suitable" areas with the highest WPD values. On the other hand, if policy makers are focused on environmental protection, areas with strong adherence to the buffer zones around environmental factors can be emphasized to deprioritize projects in ecologically sensitive zones.

Suitability Class	Area (km^2)	Area (%)
Not Suitable	2428.02	10.16
Least Suitable	11339.51	47.45
Moderately Suitable	6387.89	26.73
Suitable	2289.41	9.58
Most Suitable	1452.99	6.08

Table 3. Final suitability and area coverage.

The most suitable areas can be found in the municipalities of Sta. Ana, Gonzaga, Sta. Teresita, Buguey, Aparri, Claveria, and Sanchez Mira. Currently, there are no onshore wind farms development in these areas but there are existing offshore wind farms in Aparri and one onshore wind service contract awarded in Sta. Ana in March 2024. The summary of the results is shown in Table 3.

3.4. Validation of Results

As of March 2024, the Department of Energy only awarded one onshore wind farm service contract in the province to Mainstream Renewable Power Philippines Corporation for an onshore wind farm project (DOE, 2024). The project is in its pre-development stage with a potential capacity of 100 MW and is expected to be situated in Sta. Ana, Cagayan. With this information, the results should be validated accordingly. The suitability map of the proposed area of installation is shown in Figure 6.

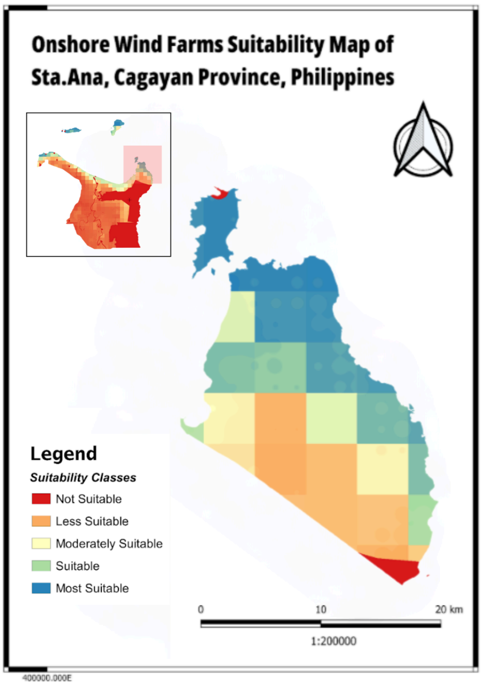

Figure 6. Suitability map of Sta. Ana, Cagayan.

Figure 6 was clipped from the final suitability map as shown in Figure 5. The suitability map shows that there are 1.94% unsuitable and 11.71% least suitable areas in Sta. Ana, Cagayan. Meanwhile, there are 28.73% moderately suitable, 25.62% suitable and 32.01% most suitable areas in the proposed installation area. With the location of the wind energy service contract, it is viable that the development company will utilize the suitable and most suitable areas. Furthermore, the proposed installation area has a low percentage of unsuitable areas which makes it more appealing for onshore wind farm developments due to less legal constraints. The proposed capacity of the onshore wind farm is 100 MW and the Center for Sustainable Systems (2023) suggested that 4 MW of power capacity is equivalent to 1 square kilometer of land. This means that the wind service contract will account for an estimated 25 square kilometer area. In accordance with this, the most suitable areas in Sta. Ana, Cagayan can be maximized for the installation of this onshore wind farm project since it accounts to an area of 137.50 square kilometers. In line with this, the results are validated accordingly since the wind service contracts of Mainstream Renewable Power Philippines Corporation are situated in the most suitable areas of the final suitability map. Furthermore, this shows that the suitability map captures the decision-making perspective of the private sector and renewable energy developers.

3.5. Comparative Analysis of AHP and PROMETHEE II

The use of MCDA methods such as AHP and PROMETHEE II considers the multifaceted nature of onshore wind farm projects and the need to balance economic importance, community engagement, and environmental sustainability. To compare the results of both methods, the criteria maps are shown in Figure 4 and Figure 7.

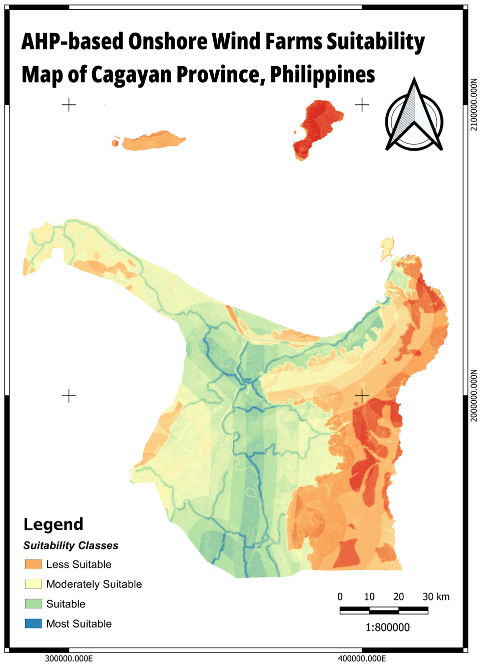

Figure 7. AHP suitability map based on criteria only

As shown in Subsection 3.2 and Figure 7 of this study, there area 79% and 31.19% moderately suitable areas according to AHP and PROMETHEE II calculations. Considering the remaining areas, there are 4.97% and 15.94% least suitable and 40.ations for both MCDA methods, there are 51.45% and 43.71% suitable and 2.80% and 9.16% most suitable areas, respectively. The results of the suitability maps show that the AHP and PROMETHEE II have significant similarities especially in the location of the most suitable areas which are in the same municipalities as mentioned in Subsection 3.3.

Based on Figure 7, it can also be seen that the least suitable areas are found on the rightmost part of Cagayan Province where the Sierra Madre mountain ranges are located. These results show that both MCDA methods handle multiple considerations almost equally. However, AHP has weaknesses that can be addressed by PROMETHEE II especially based on its complexity and limited pairwise comparisons, underlying value judgements, and treatment of inconsistencies.

Based on its complexity, AHP is reliant on the decision makers' determination of pairwise comparisons (Balali et al., 2014). The problem with heavy reliance on the decision makers' preferences is that they have their biases on their own field of study. For instance, an expert on environmental policies will most probably give higher importance or weightage to environmental criteria than physical criteria. This shows that sometimes the biases of the decision makers result in inconsistent criteria weights. To address this problem, PROMETHEE II simplifies the decision-making process by applying preference functions to each criterion. For example, the environmental criteria such as protected areas and key biodiversity areas can be a V-shape preference which indicates that strong preference is applied to criterion with minimal environmental impact. On the other hand, physical criteria such as slope or surface roughness can be a linear preference function since a gradual decrease in physical attributes decreases its preferences.

AHP is considered as a complete aggregation method (Roy and Bouyssou, 1993). This means that it can handle multiple inputs of criteria to come up with a final ranking of alternatives. The problem with AHP aggregation is its compensation on alternatives with simultaneous occurrence of good and bad criteria scores (Macharis, 2004). For instance, site A has excellent wind conditions but is located near built-up areas which causes noise and flickering pollution concerns. Meanwhile, site B has moderate wind conditions but is situated significantly away from built-up areas. Due to AHP aggregation, since site A has excellent wind conditions which means higher score but low score on minimizing noise and flickering pollution, it might still rank higher than site B with moderate scores but excels in avoiding community disturbances. This example describes the compensatory effects of AHP which loses significant information due to aggregation. PROMETHEE II is proven to avoid these trade-offs because the relationship of the alternatives is enriched using the positive and negative outranking flows.

PROMETHEE II treats the inconsistencies of AHP especially in consistency requirements. AHP relies on the high-level of consistency in the pairwise comparisons while PROMETHEE II does not rely on it at all (Balali et al., 2014). This method bypasses the need to check for consistency ratio which deems the results of AHP survey usable or not. On the other hand, PROMETHEE II also allows incomparability situations wherein several alternatives can be considered equally good based on certain conditions. This flexibility accounts to the real-world decision-making process because decision makers sometimes consider certain criteria to be equal (Balali et al., 2014). AHP cannot handle this information because decision makers must rank criteria based on scale ranking. By these situations, PROMETHEE II can produce a more realistic and accurate representation of decision makers' preferences that can handle their uncertainties and ambiguities in the decision-making process.

4. Conclusions

The proposed framework is one of the first to combine AHP and PROMETHEE II and integrate them with GIS methods to generate an onshore wind farm suitability mapping. This study provided an onshore wind farm suitability map of the study area that can help with their future wind energy projects. In addition, limited studies have been conducted about the use of PROMETHEE II in the context of the Philippines and this study is one of the few that was conducted. Furthermore, the methods presented in this study can be used as a more intensive and strategic land suitability and planning tool by decision-makers for onshore wind farm siting developments and can be a guide for future large-scale mapping at regional, or even national levels. This study can be accepted as a model for onshore wind farm suitability analysis in the Philippines and using appropriate criteria, it can also be adopted by other study areas.

An important conclusion from the results suggests that there is much room for improvement to exploit the sustainability provided by wind energy utilization. In the case of the Philippines, to achieve the country's vision of 50% renewable energy sources by 2040, it is viable that they use strategic tools such as the proposed framework. In line with this, addressing the encountered limitations of this study is also important. To increase the accuracy of this project, recent studies using MCDA methods for wind farms suitability analysis use wind speed and other wind specifications as a part of their decision criteria. Future researchers can integrate wind specifications in their study criteria to get each specific criterion weights. In addition, other researchers should integrate a WPD map with more refined resolution, preferably with the same resolution as the datasets to ensure consistency. Moreover, natural disaster data (flood-prone areas, landslide-prone areas, earthquake-prone areas, etc.) must also be included in the onshore wind farm suitability analysis. Due to the limited number of wind service contracts in the study area, the validation of the results should be investigated more by integrating more licenses and existing wind farms in the proposed study area.

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