Balancing Renewable Energy Development and Biodiversity Conservation: An Interdisciplinary Multi-Criteria Decision-Making Approach for Wind Power Siting in China

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EXECUTIVE SUMMARY

The world stands at the critical intersection of two escalating environmental crises: climate change and biodiversity loss (UN, 2022). While renewable energy is an essential strategy for climate mitigation, its expansion threatens to compromise biodiversity. In China, where wind and solar power have grown dramatically over the past decade, renewable energy infrastructure is increasingly reaching ecologically sensitive areas. This master's project explores how spatial decision-making tools can support the dual objectives of renewable energy development and biodiversity conservation by identifying optimal siting strategies for offshore wind and inland solar power infrastructure.

This study aims to answer a key question: *How can we optimize renewable energy development while minimizing adverse impacts on biodiversity, particularly migratory waterbirds in coastal China?* To address this, the research integrates a Geographic Information Systems (GIS) spatial analysis with a Multi-Criteria Decision-Making (MCDM) approach, focusing particularly on the Chinese Exclusive Economic Zone (EEZ) and mainland coastal provinces.

The significance of this work lies in its interdisciplinary methodology and its direct policy relevance. The project not only builds on established MCDM-GIS frameworks but introduces a novel ecological dimension through high-resolution GPS tracking data from 38 Black-faced Spoonbills (*Platalea minor*)—a migratory, endangered species. This unique dataset allows for the incorporation of dynamic bird movement into siting analysis, thus refining our understanding of species-infrastructure interactions.

The objectives of this research are the following:

1. Quantitatively assess renewable energy development potential within and outside ecologically sensitive areas to identify whether high development potential necessarily overlaps with ecologically sensitive zones.
2. Evaluate the current spatial performance of existing wind and solar energy infrastructure.
3. Develop MCDM maps to support decision-making under different scenarios of ecological, economic, and social priorities.

The project area includes China's coastal provinces and its marine EEZ. Inland solar PV was examined in mainland coastal regions, while offshore wind analysis focused on the EEZ. The GIS analysis involved three main data categories: ecological (e.g., Important Bird Areas, ecological redline regions), infrastructure (e.g., existing wind turbines, PV plants), and development potential indices (i.e. the measurement of energy yield or income that a location can generate).

Development potential inside and outside ecological sensitive areas was compared using Kolmogorov-Smirnov tests. Ecological regions were defined with 4 km buffers around nationally recognized conservation areas, and surrounding zones were analyzed using 8 km, 10 km, and 15 km control buffers to assess gradient trade-offs. The performance of current wind and solar installations was assessed by mapping their overlap with sensitive ecological areas and evaluating their development potential scores.

A second phase employed adjusted Analytic Hierarchy Process (AHP) approach to build a flexible MCDM model for offshore wind siting in EEZ. After removing constraint zones (e.g., nature reserves, areas deeper than 1000m), seven key criteria were selected for offshore wind siting: wind speed, ocean depth, seabed slope, distance to the power grid, LCOE, local firm activity (as a social proxy), and distance to ecologically important areas. These were normalized and weighted under three planning scenarios: Balanced, Ecological and Social Prioritized, and Economic and Construction Feasibility Prioritized.

Our key findings include:

1. **Energy Potential in Ecological Areas**: Offshore wind potential within ecologically important areas often falls in a moderate range, avoiding extremely low-yield sites but rarely aligning with the highest-yield areas. Inland solar sites showed a similar trend. Thus, ecological areas are not consistently the most energy-rich, undermining the assumption that ecological harm is a necessary cost for energy gain.
2. **Suboptimal Current Siting**: A significant number of current wind turbines and solar panels are located within ecologically sensitive regions, despite not corresponding to high development potential. For example, 9.15% of offshore wind turbines are within ecologically important areas, many in low-yield zones, suggesting inefficient or poorly regulated siting.
3. **Multi-Criteria Suitability Maps**: The scenario-weighted suitability maps revealed strong spatial differences. Provinces like Liaoning, Zhejiang, and Fujian consistently emerged as high-potential, relatively low-conflict zones across all three scenarios. Shandong Province was rated higher in the Ecological and Social scenario, emphasizing its future potential under conservation-centered planning. In contrast, near-shore areas favorable in the economic scenario were often avoided in the ecological scenario, revealing the trade-offs in siting priorities.

This research provides a replicable methodology for integrating biodiversity considerations into renewable energy planning at a national scale. By illustrating that high development potential does not inherently conflict with biodiversity protection, the study calls for recalibrating decision-making to better reflect ecological values.

It also reveals gaps in China's current renewable energy siting policies, which permitting infrastructure in sensitive regions has been found in a significant level due to limited enforcement and systematic planning. This highlights the need for fine-scale ecological data, dynamic wildlife movement monitoring, and scenario-based planning tools in policy reform. The new policy released in 2025 may improve the situation but the performance still requires further investigation.

Moreover, the study advocates for continuous siting on ecological gradients and stronger biodiversity safeguards, especially in provinces undergoing rapid offshore energy development not just because of the importance of biodiversity conservation but also for efficient revenue generation. These insights are critical for implementing more sustainable and socially acceptable energy transitions not only in China but in other biodiverse regions undergoing energy transformation.

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1. Introduction

The world faces climate change and biodiversity loss crises, where the two are interrelated through complex feedback systems (UN, 2022). Climate change has been altering the terrestrial, freshwater, and coastal ecosystems, which has led to the severe loss of unique species and increased rate of disease outbreak, wildlife mortality and climate-driven extinctions. Biodiversity loss impedes the effectiveness of forests, wetlands, and oceans in mitigating greenhouse gas emissions and speeding up climate change.   On COP28, 125 countries declare to “work together to triple the world’s installed renewable energy generation capacity to at least 11,000 GW by 2030, taking into consideration different starting points and national circumstances” (COP28, 2023). However, if not managed properly, the large-scale development of renewable energy, such as solar and wind energy, during the transition process may cause biodiversity loss. Wind turbines may negatively affect wildlife both directly through collisions and indirectly through noise pollution, habitat destruction, and decreased survival and reproduction rates of birds and bats by changing their mating and migration patterns (Lai et al., 2025; USGS Energy and Wildlife, n.d.). A quantitative study of wind turbine in China showed that 84 wind turbines may negatively decrease bird abundance by 5.27% and result in a 3.7% reduction in bird richness(Meng et al., 2024). Solar panels can also negatively affect plants and arthropod communities through land use changes and increase resistance to animal movement, thus changing species abundance in the ecosystem (Lafitte et al., 2023; Yang et al., 2024). If we only focus on climate change mitigation and selecting sites with the highest capacity of capturing solar and wind energy without considering biodiversity impact, we may not only miss the target of reducing biodiversity loss but also fail in climate change mitigation. The complex interrelationship between climate change and biodiversity loss emphasizes the importance of implementing coordinated strategies to tackle the two challenges.

Wind and solar energy development is rapidly expanding in China. In the past ten years, the Chinese wind power market has experienced rapid growth, making it the major wind energy market in the world (Yang et al., 2017). Solar power in China has a compound annual growth rate of 81% during 2010

– 2020, reaching 325.9 billion kWh solar power generation in 2021 (Zhao et al., 2022). Given the high intensity and speed of green infrastructure development, we need effective and reliable solutions to achieve sustainable energy development accounting for the impact on biodiversity. In the 1900s, the selection of sites for renewable power plants relied on conventional procedures and analytical methods. Site selection was considered a necessity to maximize efficiency in energy facilities. Choosing the optimal location can significantly increase power plant efficiency by decreasing utility and management efforts (Calzonetti and Eckert, 1981). With geospatial analytics development, site selection for renewable energy facilities nowadays uses Geographic Information Systems (GIS) and multi-criteria decision-making (MCDM), considering multiple technological, economic, sociological, and ecological factors (Asadi et al., 2023). MCDM allows decision-makers to evaluate alternatives toward different objectives based on multiple criteria. Decision-makers can also express preferences by assigning different weights to criteria. Ari et al. used three MCDM methods, stochastic multi-criteria acceptability analysis (SMAA), analytic hierarchy process (AHP), and SMAA-AHP combined approach, to identify the appropriate wind power plant sites in Turkey based on nine criteria (Arı and Gencer, 2020). The three MCDM methods suggested the same site for wind farm construction. Wang et al. also presented an MCDM model compositing AHP with fuzzy logic to select 46 solar power plant locations in Viet Nam providing a guideline for solar plant management (Wang et al., 2018). In China, the use of MCDM and GIS in green infrastructure site selection has emerged in the last few years. MCDM-GIS was used to select the tidal current power plant site in Shandong (Shao et al., 2023) and the wind farm site in Wafangdian (Xu et al., 2020). Yet, these studies mainly focused on engineering and economic criteria or lacked a thorough consideration of biodiversity loss in the decision-making.

To bridge this gap, we propose a holistic approach to green infrastructure site selection, integrating ecological, social, and economic factors. A key uniqueness of this research is the incorporation of fine-resolution GPS tracking data (2019–2023) from 38 Black-faced Spoonbills (*Platalea minor*), covering 65 flight tracks. Unlike previous studies, which rely on static habitat maps, our approach captures real-time migratory behaviors, allowing for a more precise assessment of bird-wind turbine interactions. Only flight segments exceeding 30 minutes at speeds above 2.5 m/s were included in the analysis, ensuring that only critical migratory movements were considered.

Additionally, this study conducts a newly searched policy analysis of China's wind energy policies, focusing on ecological regions and technical constraints. While China has introduced policies aimed at mitigating the environmental impacts of renewable energy, violations and conflicts with biodiversity conservation persist. The current regulatory framework lacks fine-scale ecological criteria, leading to wind farms being developed in areas critical for migratory birds. This highlights the need to assess whether a true balance between biodiversity conservation and renewable energy expansion is achievable or if trade-offs remain unavoidable. By systematically integrating policy constraints and ecological data, this study seeks to formulate a sustainable solution to resolve the conflicts between biodiversity conservation and renewable energy development.

This project aims to answer the following overarching question:

What are the appropriate sites for green infrastructure construction given the effect on biodiversity loss and economic development? As a focus on migratory waterbirds, our question can also be framed as how to optimize the capture of renewable energy with minimum negative impact to migratory waterbirds?

With the following sub-questions:

1. Is there a difference in the development potential of renewable energy inside and outside ecologically sensitive regions, where development potential can be defined as how much energy or income can a location generate considering the resource availability, transportation and land use (Deng et al., 2024; Oakleaf et al., 2019)?
2. How are the existing wind farm and photovoltaic system siting performing?
    a. What percentage of the existing sites have of high development potential?
    b. What percentage of the existing sites are located within ecological sensitive regions?

3. If constructing renewable infrastructure within the ecological sensitive regions does not necessary mean having higher economic benefits, how we should re-assign the weight of ecological benefits in our site selection decision making to both capture renewable energy efficiently and ensure waterbirds are being protected?

We address the questions through two main processes, GIS analysis using current available energy development indices (to answer sub-question 1 and 2), and multi-criteria decision making for wind farm site selection (to answer sub-question 3).

2. Methods

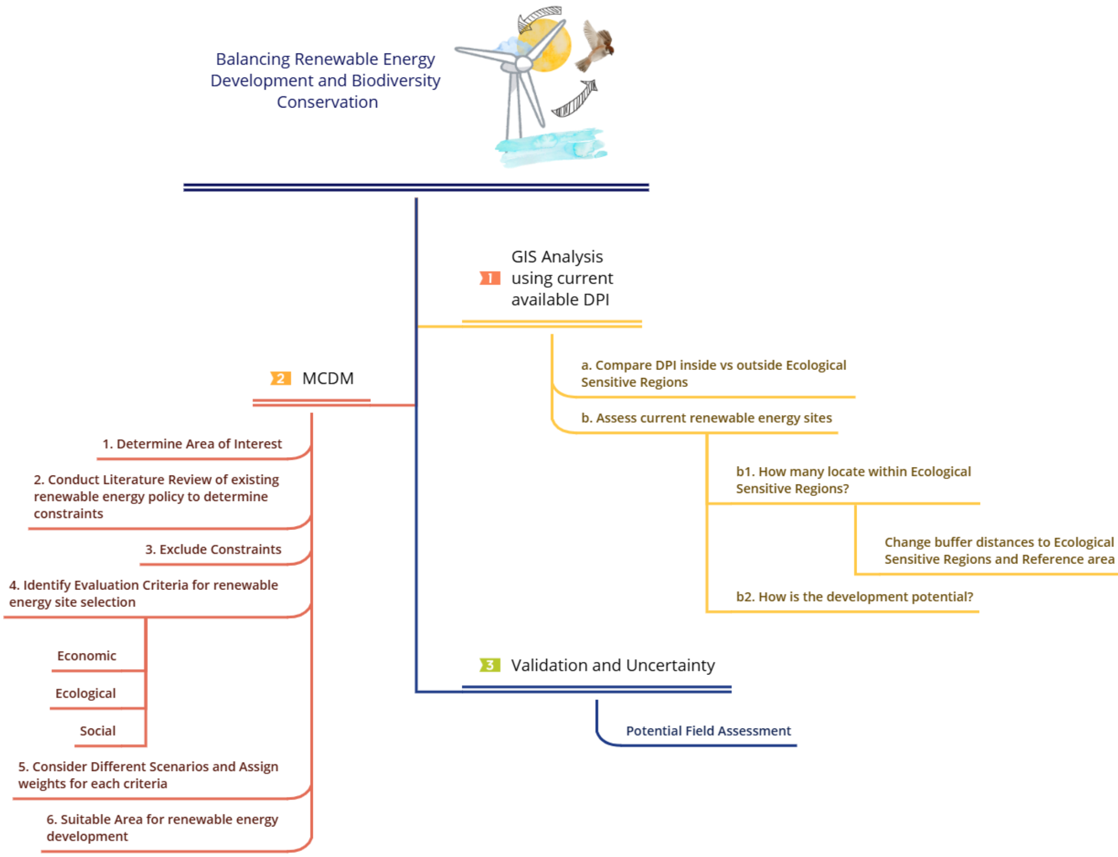
2.1 Study Area

We used coastal provinces in China mainland as our focus because the conflict between renewable energy development and wildlife conservation are more intense in coastal provinces with limited land available, fast-growing economy and great waterbird diversity.

As the field of offshore wind is developing prominently, the siting of offshore wind is particularly essential for renewable energy companies and policy makers. In this research, we focused on Chinese Exclusive Economic Zone (Flanders Marine Institute (VLIZ), Belgium, 2023) to provide insights on offshore wind siting including how the current offshore wind turbine performing, and where the offshore wind should locate. Any overlapping claim zones for different countries were not considered to avoid misinterpretation and misunderstanding.

The coastal area of inland photovoltaic system were analyzed because offshore solar PV or floating solar has just started to develop in China, some of which are still in testing phase (Wen and Lin, 2024). The ecological impacts of offshore PV were merely understood with limited research, therefore, focusing on inland PV could provide real impact on the industries and policy.

2.2 Overall Workflow



Outline of the workflow for this project

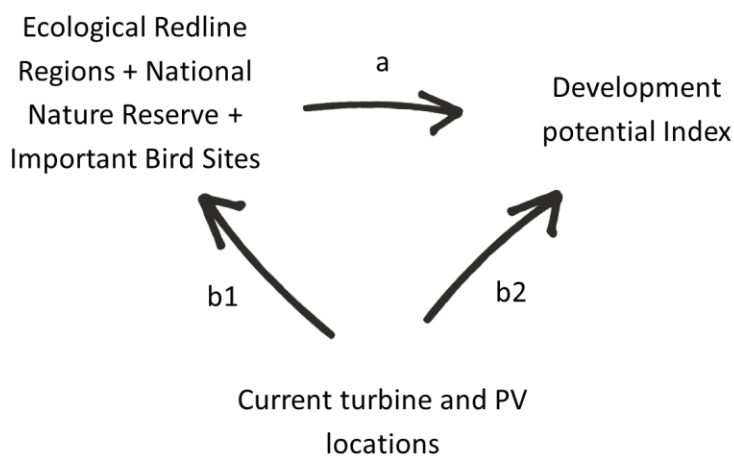
Figure 1

This study consists of two main parts: GIS analysis (Part 1) and MCDM (Part 2). Due to the limited time, we didn't finish field assessment and validation but we plan to do it in the future after graduation.

To understand how biodiversity may conflict with renewable energy development, we first compared the development potentials inside and outside Ecological Sensitive Regions. Development potential index (DPI) represents how much energy that the location can generate, considering both resource availability and development feasibility (Oakleaf et al., 2019). Comparing the DPI values inside and outside areas with high ecological values would help us understand whether a place with ecological values also has higher renewable energy development potential. We defined the areas inside Ecological Sensitive Regions as 4 km buffer distance to National Nature Reserves, Ecological Redline Areas, and Important Bird Sites whereas the areas outside are 8 km, 10 km and 15 km buffer distance to these Ecological Sensitive Regions. After computing DPI both inside and outside Ecological Sensitive Regions, the performance of existing renewable energy sites was then assessed in two trajectories:

1) where and how many of these existing sites are within ecological sensitive regions. This is to analyze the current conflict level between economic development and ecological benefits. (Figure 2a)
2) and how the development potential is at existing sites to assess the economic benefits that the existing sites can provide (Figure 2b)

2.3 Preliminary GIS Analysis



The nexus between sub-questions to assess the performance of current renewable energy site selection and explore the conflict between ecological importance and development potential

Figure 2

The questions I want to ask are inter-related. We have collected three groups of datasets, including ecological datasets, development potential (energy datasets) and current renewable energy locations.

Three main sets of datasets are used including ecological data, renewable sites, and development potential dataset (Table 1). National Nature Reserves, Important Bird Sites and Ecological Redline Region (ECR) data are merged into the area of ecological importance. The development potential within and outside the ecological important area are compared using Kolmogorov-Smirnov (K-S) test because of the uniqueness of K-S test including comparing the underlying distribution rather than just mean and median and its non-parametric feature. The buffer distances of ecological important area were set as 4km based on the influence of wind turbines on bird population (Choi et al., 2022) whereas the buffer distance of control group outside the buffer region as development potential comparisons were set as 8km, 10km and 15km to make sure the control groups are valid and consistent. Increased buffer distance may influence the results by double counting development potential when buffer areas overlap. Therefore, the distances were chosen to balancing the tradeoff between minimizing the overlapping effect of different buffer areas when ecological important regions locate close to one another, and providing enough development potential difference from ecological important area.

We used this gradient-based siting analysis to compare development potential within and outside ecological important area because of the strategies which companies would take. Avoiding ecologically sensitive areas has been recognized as the best practice to minimize environmental impact (Bennun et al., 2021). Therefore, when companies own lands that includes such areas, strategically siting the renewable energy infrastructure outside these ecological important areas but still within their property boundaries is advisable. By implementing the conservation buffers, the companies can also mitigate the conflicts between renewable energy and biodiversity conservation and providing ecological benefits suggested by U.S. Department of Agriculture's Forest Service (Bentrup, 2008). Gradient-based approach has been used in wind farm layout optimization (Criado Risco et al., 2024) but haven’t been used for ecological settings.

The current wind turbine and solar panel locations were then analyzed. The development potential for both wind farms and solar PV were extracted from current locations and compared between area of ecological important and the total area of interest. The total areas of interest differ between renewable energy types, for inland solar analysis which means coastal provinces in China, whereas for offshore wind which means Chinese Exclusive Economic Zone.

Table 1

Data sources used in GIS analysis

Dimensions	Datasets	Definition	References
Administrative	Exclusive Economic Zone of China	Where China has exclusive rights regarding the exploration and use of marine resources based on 1982 United Nation Convention on the Law of the Sea	(Flanders Marine Institute (VLIZ), Belgium, 2023)
	Coastal provinces	The boundary of Liaoning, Hebei, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi, and Hainan Province	(Esri et al., 2022)
Ecological	National Nature Reserve	Boundary defined by Ministry of Environment Protection of China	(Hu et al., 2017)
	Important Bird Sites	"Either coastal sites of international importance for waterbird species (i.e., meeting Ramsar Convention listing criterion 6, >1% of the flyway population recorded at the site) or sites of international importance for shorebird species in the East Asian–Australasian Flyway"	(Choi et al., 2022)
	Ecological Redline Regions	The areas pose special ecological functions (e.g. water retention, biodiversity conservation, protection against soil erosion) that must be strictly protected by law	(Choi et al., 2022)

	GPS-tracking data of black-faced spoonbill	We used 65 GPS tracking data of 38 blackfaced spoonbill individuals from 2019-2023 for southward migration only. Details on methodology can be found in Lai et al.'s paper.	(Lai et al., 2025)
Energy	Current PV power plant locations	Power plants present from 2010 to 2022 derived from Sentinel 2, Landsat image series, land use data and processed via deep learning algorisms	(Chen et al., 2024)
	Current wind turbine locations	"Detections that are likely offshore infrastructure from 2017 to 2021 (monthly), detected using Sentinel-1 SAR imagery and classified using deep learning (based on SAR and optical images)"	(Paolo et al., 2024)
Economic	Development Potential Index (inland solar)	Measurement of development potential for energy sectors using GIS within MCDA procedures (GIS-MCDA), specifically AHP in combination with WLC, compelling resource, biophysical and land use constraints. The uncertainty of DPI fell below 25%.	(Oakleaf et al., 2019)
	Development Potential Index (offshore wind)	Calculated by wind power generation potential and carbon reduction potential.	(Deng et al., 2024)

2.4 Multi-Criteria Decision Making via APH

To better support the decision making of wind turbine siting in Chinese Exclusive Economic Zone, we used a multi-criteria decision-making approach with Analytic Hierarchy Process (AHP) integrated with GIS analysis. AHP provides an integration of both qualitative and quantitative criteria, where transparent pairwise comparisons and expert-informed weight variation are allowed (Saaty, 1987). It is also effective when criteria are difficult to compare directly including technical, ecological and social considerations.

The framework we adapted from AHP takes the following steps: 1) determining the decision goal and criteria/constraints we want to implement; 2) excluding the area where the constraints were met; 3) structuring a hierarchy of the criteria based on our goal; 4) computing the relative weights for each criterion; 5) adjusting the weights in different scenarios (ecological and social impact prioritized, and economic and construction costs prioritized); 6) aggregating the weighted criteria via Weighted Linear Combination (WLC) to create the final map. WLC assumed each criterion affect the final outcome in a linear and independent way relative to the assigned weight, meaning the values in each criterion contribute linearly to the final score for simplicity (Malczewski and Rinner, 2015). Please also note that we skipped the step of pairwise comparison. Instead, we used the weights calculated in a previous paper (Wang et al., 2022) and adjust the weights to create three scenarios.

We will go through each step in the following sections where the first section, policy analysis and constraints determination, mainly focused on finding the constraints and excluding non-realistic area for new wind farms.

2.4.1 Policy Analysis and Constraints Determination

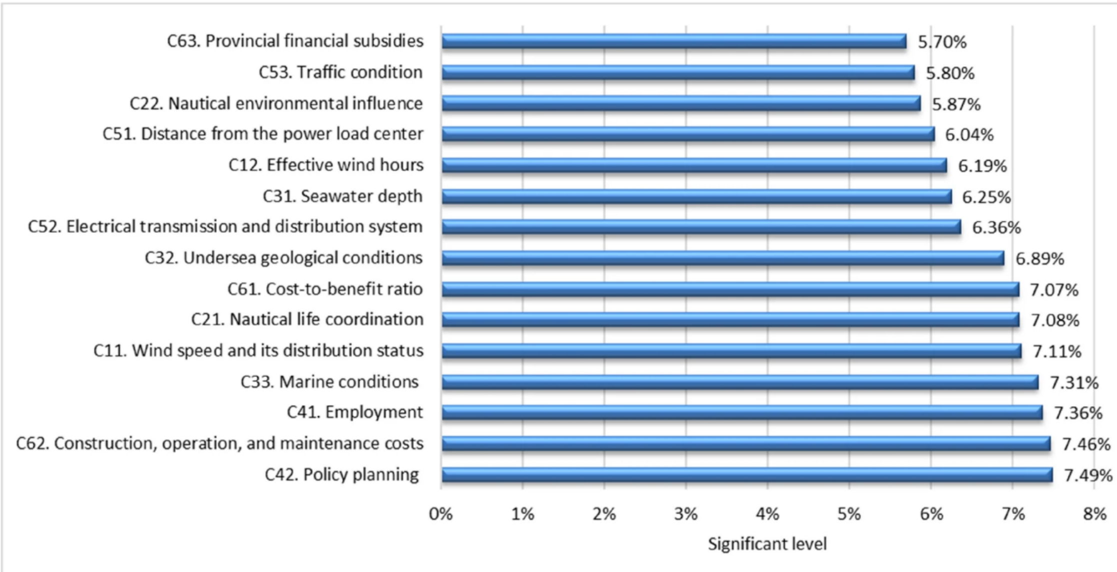
According to "The Notice of the Ministry of Natural Resources on Further Strengthening Sea Use Management for Offshore Wind Power Projects"(自然资源部, 2024), constructing wind energy infrastructure in Ecological Redline Areas, Nature Reserves, important coastal wetlands, important bird corridors and habitats are strictly forbidden. This notice came into effect on January 5th, 2025. We thus considered Ecological Redline Area and Nature Reserves as two of the constraints for building offshore wind turbines. The notice also restricted the newly constructed wind energy infrastructure to be laid out beyond 30 km off the shoreline **or** in the areas where water depth is more than 30 meters. If the water depth is more than 30 meters, the distance from shoreline should not be less than 10 km as well. These restrictions have also been considered in our MCDM analysis.

Existing Infrastructure were excluded as well to focus on the siting of newly constructed wind turbines. A buffer distance of 1 km was chosen which is approximately the minimal distance between turbines (Gupta, 2016).

Based on Energy Sector Management Assistance Program's report developed by the World Back and 21 development partners, The maximum sea depth a conventional fixed wind turbine can locate is 50 m whereas a floating turbine can be developed up to 1000 m (ESMAP, 2019). Because we don't have a specific preference on the type of offshore wind turbine, we set the constraint of sea depth to 1000 m. All the area where water depth is greater than 1000 m was excluded in our study.

2.4.2 Evaluation Criteria and Weight Assignment

After determining the constraints and the area where wind turbine will not locate, we start to find the evaluation criteria while assessing them by reviewing 16 criteria proposed by Wang et al. (2022). The most influential criteria shown in Figure 3 were C42 Policy Planning (7.49%), C62 Construction, Operation, and Maintenance Costs (7.46%), and C41 Employment (7.36%), whereas the least influential were C63 Provincial Financial Subsidies (5.70%), C53 Traffic Condition (5.80%), and C22 Nautical Environmental Influence (5.87%). We didn't include all of the 16 criteria in our analysis, mostly due to the limitation of spatial ranges or time variation in the publicly available datasets. For instance, C21 Nautical Life Coordination was not included in our analysis because marine functional zoning data is not fully available nationwide. Yet, we did a post-hoc overlay analysis for Jiangsu Province using the province level dataset we got. C62 Construction, Operation and Maintenance costs were indirectly reflected through seabed slope, ocean depth and IEC-Fatigue Loads classes, which is a classification for wind speed and turbulence recognized in the industry. The criteria of marine conditions (C33) were not included due to a lack of high-resolution, public oceanographic data but is recommended for future onsite investigation when micro-planning takes place. C63 (Provincial Financial Subsidies) was also not considered in our study due to its strong temporal variability but we suggest incorporating the data on a case-by-case basis depending on regional policy contexts.



The significant level of criteria in offshore wind farm siting (Wang et al., 2022).

Figure 3

A total of 15 experts with more than 10 years of professional experience in different field were interviewed. Their expertise includes offshore wind farm construction, engineering, hydrology, social sciences and environmental sciences.

We used seven criteria after finalized where reliable, high-resolution, and national datasets are available (Table 2). These includes wind speed, ocean depth, seabed slope, distance to the power grid, levelized cost of energy (LCOE), firm activity (as a proxy for local social impact), and distance to ecologically sensitive areas (compiled from 4 datasets including protected areas, ecological redlines, IBAs, and GPS-tracked bird paths)

The seabed slope was derived from the GEBCO bathymetry dataset using the *Slope* function in ArcGIS Pro to calculate gradient, serving as a proxy for undersea geological complexity and construction difficulty. Distance-based criteria such as distance to grid infrastructure and ecological sensitive zones were calculated using Euclidean distance tools in ArcGIS. All raster inputs were normalized on a 0–1 scale to ensure comparability for the weighted overlay analysis. Each selected criterion was matched to the closest corresponding criteria in Wang et al.'s crisp AHP weights in the Table 11 in their paper.

Table 2

Criteria being used, their definition and data sources

Dimensions	Criteria	Definition	Criteria from AHP Paper Mapping (Wang et al., 2022)	References
Economic	Levelized Cost of Electricity (LCOE)	Financial cost-effectiveness of offshore wind production	C61: Cost-to-benefit ratio	(An et al., 2025)
Social	Local Economic and Employment Status	Firm numbers in 2015 for each district/county as an indicator of local employment needs and social benefit potential. The firms in each district/county were summarized (国家地理信息公共服务平台, 2024). The firm activity of the closest district/county to each area of interest were assessed.	C41: Employment	(Dong et al., 2021)
Economic	Ocean Depth	Seabed depth affecting turbine construction and cost	C31: Seawater depth	(GEBCO Bathymetric Compilation Group 2024, 2024)

Economic	Seabed Slope	Gradient of the seafloor affecting construction feasibility	C32: Undersea geological conditions	Derived from Bathymetry dataset using Slope function in ArcGIS Pro
Economic	Wind Speed	Average offshore wind speed at 150 m and 200 m, proxy for energy potential. Previous studies have been using lower height (80 m,100 m, 120m) but after consulting with industrial partners we decided to use higher height accounting for the future wind turbine market.	C11: Wind speed and its distribution	(Larsén et al., 2022)
Ecological	Distance to Ecological Important Areas	Distance to the merged raster of Nature reserves, ecological redline (Ministry of Environmental Protection), 4km buffer zone around Important Bird Sites (BirdLife), and GPS tracking data of black-faced spoonbill. We chose a threshold of 0.002 for the probability of normalized black-faced spoonbill occupancy.	C22: Nautical environmental influence	(Hu et al., 2017; Choi et al., 2022; Lai et al., 2025)
Economic	Distance to Grid	The distance to distribution and transmission line network	C52: Electrical transmission system	(Open Street Map, 2021)

While most weights for the Balanced scenario were derived directly from normalized crisp weights, we made two key adjustments to better represent compound factors. First, the weight for LCOE was increased to incorporate half the weights from C12 (Effective Wind Hours) in addition to C61 (Cost-to-benefit ratio), as LCOE implicitly reflects energy generation efficiency and economic feasibility. Second, the weight for Seabed Slope was increased by adding half the weights from C62 (Construction &

Maintenance Costs), recognizing its dual role in capturing seabed suitability and long-term maintenance challenges. After recalculating and renormalizing the total weight distribution, we updated the Balanced weights accordingly.

To refine the Eco+Social and Economic+Construction scenarios, we used a multiplier-based adjustment strategy guided by conceptual priorities. The Eco+Social scenario emphasized ecological and social values by boosting the weights of firm activity and ecological sensitive areas (multipliers: 1.5 and 1.5, respectively), while de-emphasizing construction and cost-related factors like LCOE (0.5), wind speed (0.8), depth (0.9), slope (0.9), and distance to grid (0.9). Conversely, the Economic+Construction scenario prioritized cost-efficiency and feasibility by increasing weights for LCOE (1.3), wind speed (1.2), seabed slope (1.1), ocean depth (1.1), and distance to grid (1.1), while reducing the influence of firm activity (0.7) and ecological constraints (0.5). These adjustments were designed to reflect trade-offs relevant to stakeholders with varying planning goals. Final suitability scores were generated using a Weighted Linear Combination (WLC) method, which summed the product of each raster criterion and its scenario-specific weight.

The finalized weights are shown below as a table (Table 3).

Table 3

Weighted Criteria under different scenarios

Criterion	Mapped Proxy Criterion	Original Crisp Weight	Normalized Balanced Weight	Ecological + Social Weight	Economic + Construction Weight
Wind Speed	C11: Wind speed and its distribution	0.071	0.141	0.1173	0.1649
Ocean Depth	C31: Seawater depth	0.062	0.1231	0.1152	0.1319
Seabed Slope	Derived from C32 and C62	0.069	0.137	0.1283	0.1468

Distance to Grid	C52: Electrical transmission and distribution system	0.064	0.1271	0.119	0.1362
Distance to Ecological Imporatant Areas	C22: Nautical environmental influence	0.059	0.1172	0.1829	0.0571
LCOE	C61: Cost-to-benefit ratio + 0.5*C12	0.1045	0.2075	0.1079	0.2628
Firm Activity	C41: Employment (proxy for social impact)	0.074	0.147	0.2294	0.1003
Total Weight	-	0.5035	0.9999	1	1

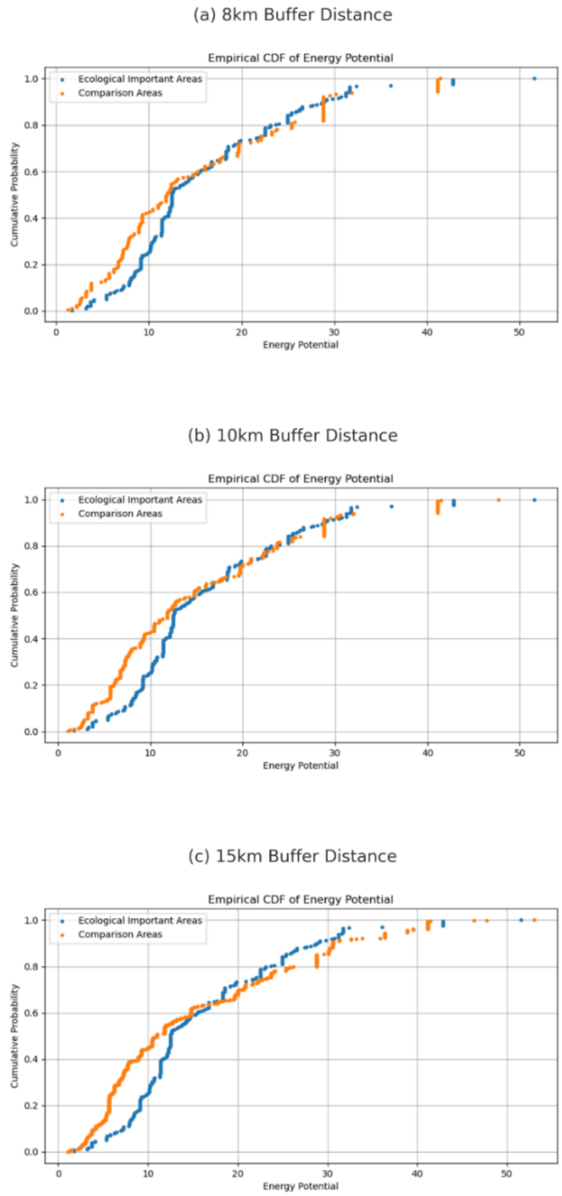
3. Results

3.1 GIS Analysis

3.1.1 Development Potential inside and outside Ecological Sensitive Regions

3.1.1.1 Offshore Wind

We used empirical cumulative distribution function (ECDF) and Kolmogorov–Smirnov test to compare the offshore wind potential in ecological important areas and the surrounding comparison regions (Figure 4).



Comparison of offshore wind energy potential in ecological important areas and nearby comparison regions

Figure 4

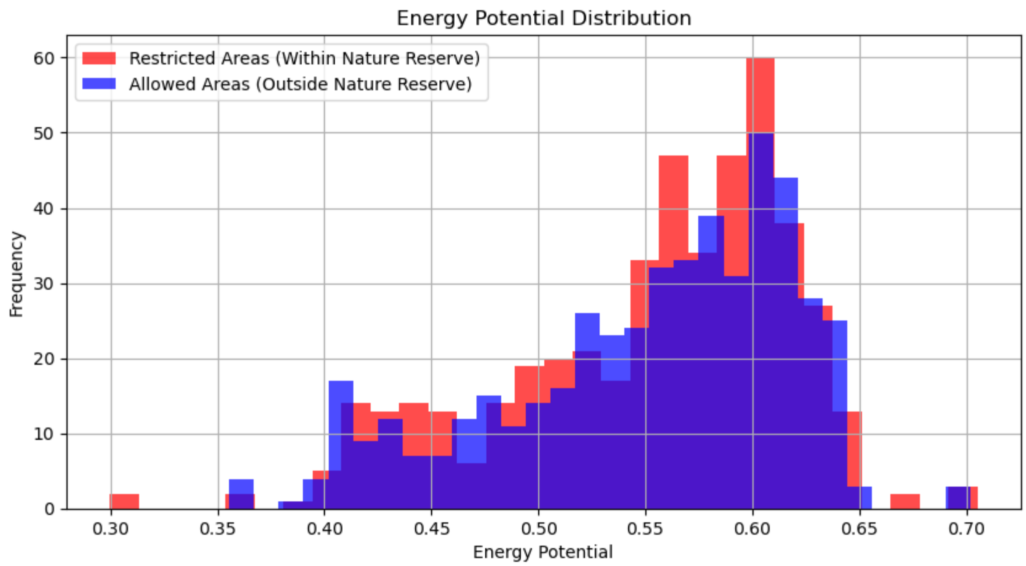
The buffer distances for the surrounding buffer areas as comparison are 8km (panel a), 10km (panel b) and 15km (panel c) respectively.

When the energy potential is low (e.g. < 15), the ECDF curves show a divergence between Ecological Important Areas (blue) and Comparison Areas (orange) across all buffer distances. The comparison areas accumulate a greater proportion in very low energy potential ranges (e.g. < 10) compared to ecological important areas. Yet, the probability of the energy potential fall within 10 to 15 range is higher for ecological important areas. This may suggest that in ecological important areas, the energy potential is relatively moderate, avoiding the very low energy potential values sites explaining why companies may choose to locate wind farms in ecological important areas.

The pattern is mostly profound when we used 8 km buffer distance to create the comparison group, where the difference between comparison group and the ecological important group is largest in the 10 to 15 energy potential range. As the buffer distance increases to 10 km and 15 km, the relatively distinction still exist but the difference become more tender because the two distributions converging more rapidly. The Kolmogorov–Smirnov (K-S) tests indicate significant differences among the two groups which correspond to what we explained in the ECDF plots. At 8km buffer, the K-S test statistic was $D(1662) = 0.172$, $p < 0.001$, indicating a significant difference between the groups. This result is consistent as the buffer distance increases to 10 km, where $D(1662) = 0.233$, $p < 0.001$, and 12 km where $D(1662) = 0.274$, $p < 0.001$. Yet, the K-S tests does not indicate where these differences occur. With the help of ECDF plots, we can see that the reason of these differences is that in low potential ranges, the ecological important areas have higher probability of locating in the 10-15 energy potential range, instead of having differences at high energy potential values.

As the energy potential increases to 20 and larger, the differences between the two groups are less profound. Among all buffer distances, the ECDF curves for ecological important areas and the surrounding groups begin to align when energy potential is high, which suggests that at high energy potential values, especially above 30, the difference between two groups becomes little.

3.1.1.2 Inland Solar



Comparison of inland solar energy potential in ecological important areas and comparison regions

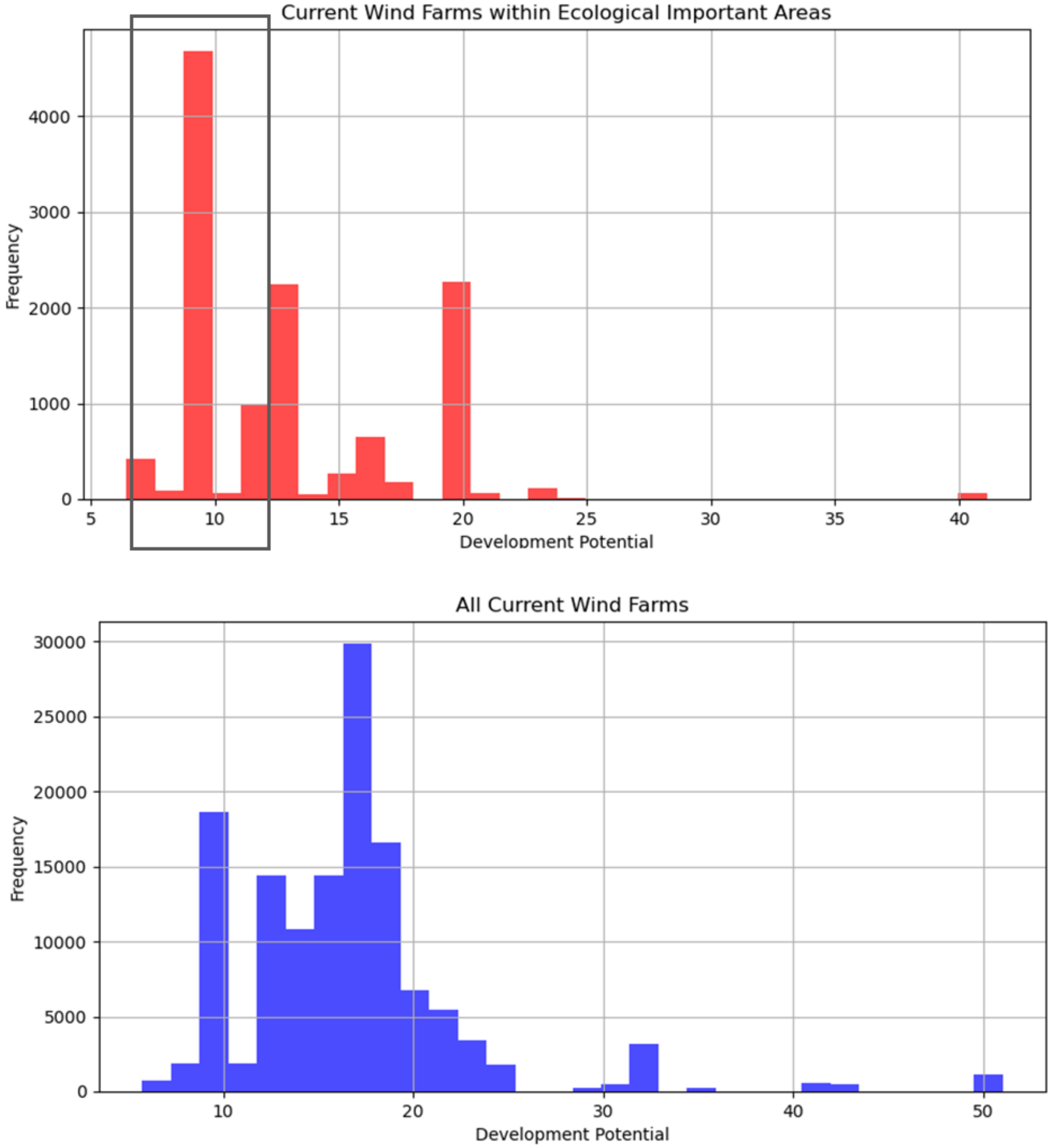
Figure 5

Inland solar shared similar trend with offshore wind where area within ecological important regions (shown as restricted areas in Figure 5) do not have higher energy potential especially at high energy potential levels.

3.1.2 Current Performance of Renewable Energy Siting

3.1.2.1 Offshore Wind

Based on our analysis, among a total of 132823 current wind farms which were constructed between 2017 to 2021, 12158 of them located inside ecological important regions. In other words, 9.15% of the current wind farms located in the area where ecological impacts became subordinate factors.



Development Potential of Current Wind Farms within Ecological Important Areas and Coastal Exclusive Economic Zone of China

Figure 6

The black square represents the high proportion of current wind farms locate within the low development potential range

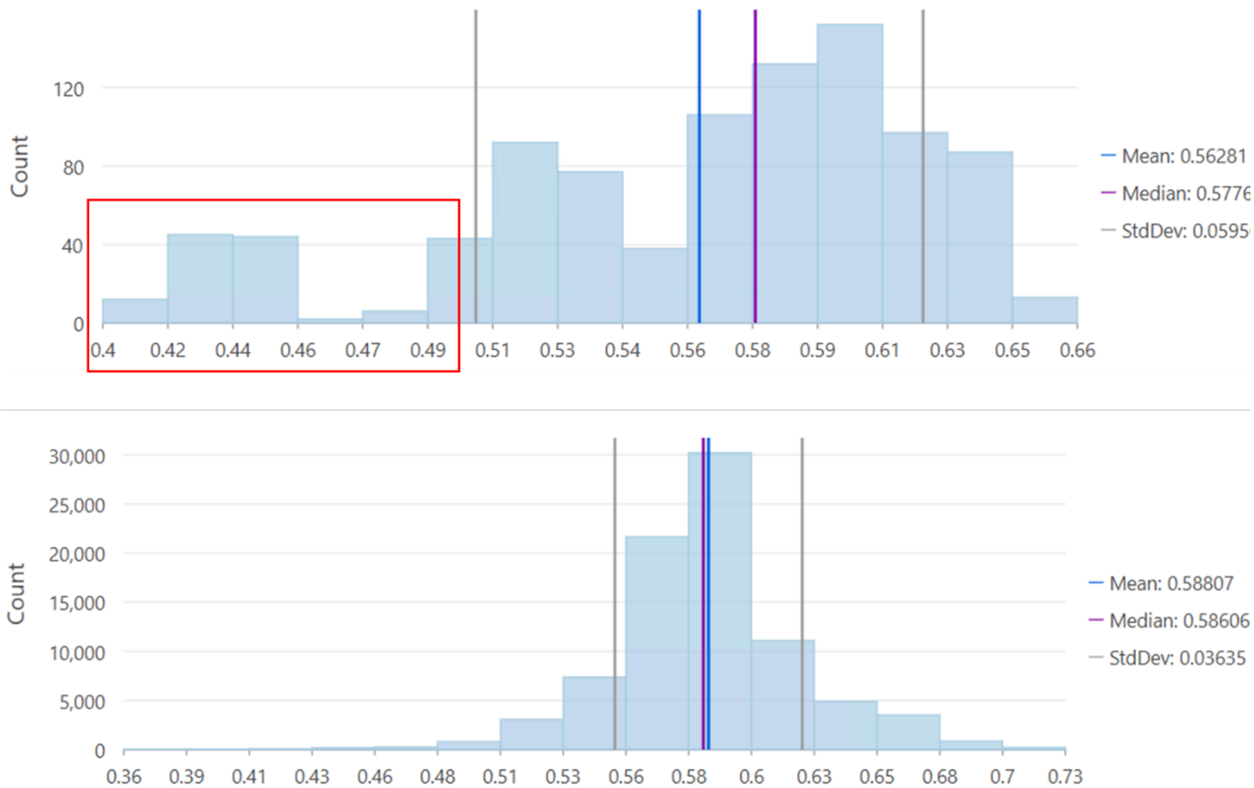
The results of analyzing the current performance of wind farm distribution also reveal the different patterns of development potential between those located within ecological important areas and the broader Exclusive Economic Zone of China (Figure 6). The histograms illustrate that a substantial proportion of the wind farms located within ecological important areas fall within low development potential range. This suggests that a considerable number of the existing wind farms are not located where it should be to maximize the wind energy production efficiency. The lower panel, representing the overall performance of current wind farms shows a broader distribution of development potential with a distribution peak about 16 which is much greater than the peak of wind farm distribution in the ecological important areas. Yet, a significant number of current wind farms still locate in some less favorable locations. This observed mismatch between ecological constraints and energy production potential raises concerns about the effectiveness of historical siting strategies.

3.1.2.2 Inland Solar

A similar trend is also observed in the siting of inland solar farms including sites that locate within ecological important areas and sites that fall within the administrative boundaries of all mainland China's coastal provinces (Figure 7). The upper panel representing the distribution of solar farms within ecological important areas shows a skewed distribution towards the lower end of the development potential spectrum. The result indicates that the solar farms in ecological sensitive areas are not necessarily located in the sites of high energy yield. On the other hand, the lower panel representing all inland solar farms in coastal provinces indicate a wider symmetric distribution suggesting that a large proportion of wind energy infrastructures outside ecological important area have been placed in locations that can also generate decent amount of energy.

All of these results of offshore wind and inland solar energy distribution emphasize the potential of sustainable energy siting. Given the current performance of existing renewable energy infrastructure siting in ecological important regions in low energy potential range and the nonvarying performance of renewable energy sites that locate within or outside ecological sensitive areas, we would argue that the weight of ecological factors in decision-making process should be increased to reduce the conflict with biodiversity conservation.

Our study applies multi-criteria decision-making methods to explicitly balance biodiversity conservation and energy development with a focus of increasing the weight of ecological factors and using more detailed and precise data in biodiversity conservation. We explored whether it is possible to redirect development toward locations that offer both high quality and quantity of renewable energy and low ecological impacts.



Development Potential of Current Inland Solar Farms within Ecological Important Areas and Coastal Provinces

Figure 7

The upper graph shows the development potential of current inland solar farms that locate within ecological important areas. The lower graph showcases the development potential of all wind farms *within the administrative boundaries of the coastal provinces. The red square represents the skewed distribution of development potential at low potential, showing that a relatively larger proportion of the inland solar farms locate in low potential ranges compared to all coastal provinces.*

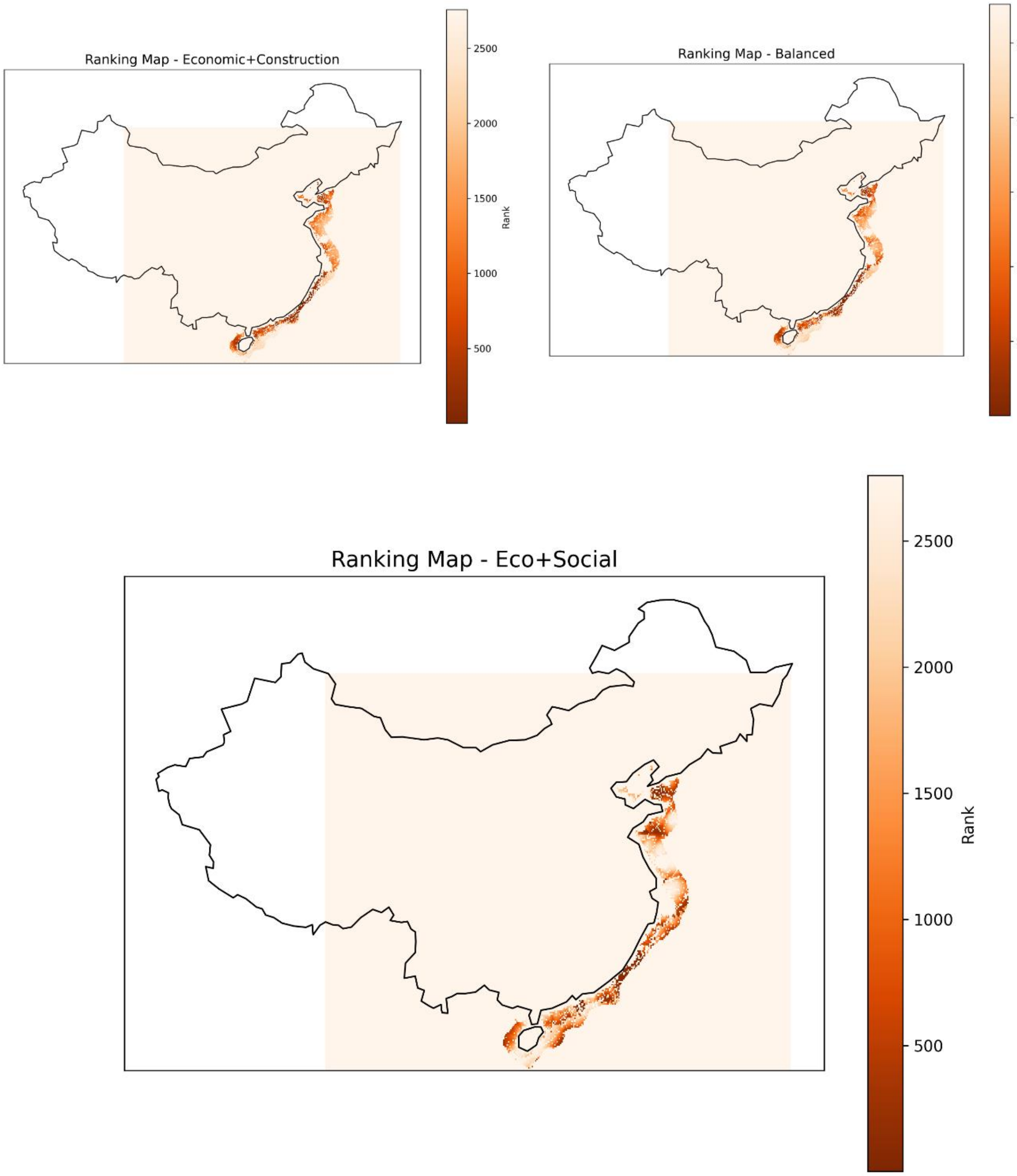
3.2 Multi-Criteria Decision Making

Our final adjusted weights for the economic and construction scenario emphasized the importance of LCOE and wind speed while de-emphasize the ecological and social criteria (Figure 8). On the other hand, distance to ecological sensitive areas and the level of firm activity are given much higher weights in the ecological and social scenario. The weights for the other four criteria have minor adjustment compared to LCOE, distance to sensitive areas and firm activity.

Weights assigned for seven criteria under three different scenarios

Figure 8

Criteria are shown on the x-axis whereas scenarios are shown on the y-axis. The darker the color is, the higher the weights assigned to each criteria meaning the more important the criteria is for the scenario.



Suitability maps under three different scenarios

Figure 9

Three scenarios were shown (upper left: Economic + Construction; upper right: Balanced; below: Ecological + Social). The darker the red is, the higher the ranking is, meaning the site is more suitable under the scenario.

3.3 Final Site Suitability Assessment

After assigning the weights and compelling maps in a linear manner, our final suitability maps delivered three major findings (Figure 9).

3.3.1 High Suitability in Liaoning, Zhejiang and Fujian Province

Across all three decision scenarios—balanced, ecology and society-focused, and economy and feasibility-focused—Liaoning, Zhejiang, and Fujian provinces consistently show as highly suitable regions for offshore wind development. This finding corresponds well with the current trajectory of offshore wind expansion in these provinces (Global Energy Monitor, 2025; Yu et al., 2024).

Liaoning Province is actively implementing several large-scale offshore wind projects, such as the Zhuanghe 5 Offshore Wind Farm (250 MW capacity), expected to become operational by 2028, and the Huayuankou Offshore Wind Farm (400 MW), anticipated to commence by 2025. These initiatives reflect Liaoning's strategic commitment to renewable energy investment and marine spatial planning.

Zhejiang Province has set ambitious targets for offshore wind, with plans to add over 10 GW of capacity by 2025. Projects such as the 504 MW Yuhuan No.2 Wind Farm and the operational 300 MW Taizhou 1 Wind Farm exemplify the province’s rapid progress and innovation in the sector.

Fujian Province has also demonstrated significant technical advancements. In 2023, the province installed the world’s first 16 MW offshore wind turbine, signaling a leap in offshore wind engineering capabilities. Fujian’s Pingtan Wind Farm, comprising 240 MW of capacity, has achieved full-grid connection, further emphasizing its leadership in high-capacity offshore development.

3.3.2 Effect of Distance to Shoreline Across Scenarios

A clear difference was observed in how distance to shoreline influences site suitability depending on the evaluation scenario. In the ecology and society-focused scenario, increased offshore distance corresponded with higher suitability scores, largely due to reduced interference with ecologically sensitive coastal habitats and bird migration pathways. In contrast, the economic and construction feasibility scenario favored sites closer to shore, as reduced distance can significantly lower infrastructure costs and transport complexity.

This dichotomy highlights the competing pressures faced by offshore wind developers and policymakers. Even within the same geographic region, different prioritizations in the multi-criteria framework (e.g., weighting ecological versus economic factors) can lead to significantly divergent site recommendations. As such, scenario-based planning remains essential for reconciling stakeholder interests and aligning development with long-term sustainability goals.

3.3.3 Emerging Potential of Shandong Province Under Ecological Prioritization

Under the ecology and social-focused scenario, Shandong Province emerged as a particularly promising region. This result is consistent with Shandong's ongoing commitment to environmentally conscious offshore wind development. The province has already completed a comprehensive marine spatial plan for offshore wind development, with 41 designated wind farm areas (Deng et al., 2024). Furthermore, Shandong has pioneered an integrated development model combining offshore wind power with marine ranching, aiming to harmonize energy infrastructure with biodiversity conservation and sustainable fisheries (Zhao et al., 2022).

4. Discussion

4.1 Main Findings

Our analysis shows that placing greater emphasis on ecological importance does not necessarily compromise economic benefits. Contrary to previous assumptions that biodiversity conservation and renewable energy development are inherently conflicting, our results indicate that it is possible to achieve a more balanced outcome when ecological criteria are properly weighted in site selection. Notably, while prior MCDM studies, such as Wang et al. (2022), allocated only 5.87% weight to environmental factors, our framework demonstrates that by using higher-resolution ecological datasets and increasing ecological weighting, the optimal siting locations change substantially—highlighting areas that would otherwise be overlooked.

Moreover, our multi-scenario analysis reveals that suitable offshore wind sites are not confined to highly sensitive ecological regions. This suggests that strategic siting adjustments can mitigate biodiversity impacts while maintaining renewable energy efficiency.

4.2 Methodological Insights

Our work highlights several important methodological considerations for future renewable energy siting. First, the difference between the two parts of our GIS analysis—comparing development potential inside versus outside ecological buffers (first part) and conducting MCDM after excluding sensitive areas (second part)—reveals different patterns. In the buffer comparison, we found minimal trade-offs; however, after ecological exclusion, competition for remaining suitable sites intensified. This divergence stems from the analytical methods: pre-excluding ecological zones reshapes the siting landscape, whereas buffer-based comparisons keep more spatial options.

Second, our model currently assumes linear decay of ecological impact with distance from sensitive areas. However, real ecological responses are unlikely to be linear. Future models should incorporate non-linear impact functions, particularly for species such as migratory waterbirds, whose vulnerability to wind infrastructure may sharply decline only beyond specific threshold distances.

Third, we observed technical dataset limitations. Seabed slope showed little variation (0–8 degrees) across much of our study area, limiting its effectiveness as a constraint. Wind speed and Levelized Cost of Energy (LCOE) layers also exhibited spatial gaps, especially farther offshore, restricting the siting model's full potential. Future efforts should prioritize improving oceanographic, wind resource, and infrastructure cost datasets, particularly in deep offshore zones.

4.3 Policy and Industry Implications

Our suitability mapping identifies Shandong Province as a future hotspot for offshore wind development. This region benefits from a convergence of moderate-to-high wind potential, manageable seabed conditions, favorable cost structures, and increasing ecological oversight under China's recent coastal protection policies. However, this result should be interpreted with caution, as the ecological data used are limited by factors such as research attention to specific regions, the availability of long-term monitoring data, and the timeliness and spatial resolution of national ecological redlines and protected area delineations.

The divergence between our two analytical approaches also highlights an important consideration for future planning: while moderate development potential is slightly favored within ecological important areas, high development potential shows little difference between inside and outside ecological important areas. This suggests that targeting the highest-potential zones could reduce conflicts between energy production and biodiversity conservation. Determining energy potential thresholds—for example, identifying the minimum energy gain that justifies development near sensitive habitats—could be an effective strategy to quantitatively assess and manage trade-offs.

Our comparison between current offshore wind infrastructure and our suitability model also reveals mismatches. Many existing projects cluster nearshore, often overlapping with sensitive ecological zones. To better manage these conflicts, future research should explicitly model energy-biodiversity trade-offs using Spatiotemporal Decision Support Systems (SDSS), such as the framework developed by Best and Halpin (2019). Their SDSS approach dynamically integrates species sensitivities and energy profitability across space and time, enabling identification of sites and operational windows that minimize ecological harm while maximizing energy gain.

Another opportunity lies in multi-use marine spatial planning, such as integrating offshore wind farms with marine ranching (e.g., algae farming, shellfish cultivation). However, while co-location could optimize spatial efficiency, it may also introduce new ecological impacts—such as changes in nutrient cycling, benthic habitat modification, and species interactions—which remain poorly understood. Quantifying these new ecological risks and incorporating them into spatial planning models will be crucial to ensure that integrated blue economy strategies do not compromise conservation goals.

4.4 Future Research Directions

Several important future research directions emerge from our findings:

1) Quantifying energy potential thresholds to better understand how much renewable energy gain justifies biodiversity risks, particularly under scenarios targeting the highest energy yield zones, is needed;

2) Modeling non-linear ecological responses to wind infrastructure proximity, particularly for migratory birds and benthic ecosystems, should be pursued to move beyond simplistic linear assumptions;

3) Extending suitability models to incorporate dynamic ecological datasets, such as seasonal migration routes and breeding grounds, can enhance temporal accuracy;

4) Refining exclusion zones by mapping continuous habitat quality gradients rather than relying solely on static protected area boundaries is another important avenue;

5) Evaluating ecological impacts of offshore wind-marine ranching co-location, and developing methods to quantify and mitigate these impacts in future multi-use spatial planning, are necessary;

6) Finally, conducting integrated spatiotemporal trade-off analyses that simultaneously optimize for energy production, ecological protection, and socio-economic benefits (Best and Halpin, 2019) will provide a more comprehensive foundation for decision-making.

In summary, our interdisciplinary GIS-MCDM framework offers a replicable foundation for balancing renewable energy expansion and biodiversity conservation. By integrating finer ecological sensitivity, energy potential thresholds, and investigating multi-use marine management strategies, more sustainable and scientifically sound offshore planning can be achieved.

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6. Appendix: Python code for MCDM analysis

```
import numpy as np
import pandas as pd
import geopandas as gpd
import rasterio
from rasterio.plot import show
from shapely.geometry import Point
from scipy.stats import rankdata
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.cm as cm

# Simplified raster loader (CRS and transform already standardized in ArcGIS)
def load_raster(file_path):
    with rasterio.open(file_path) as src:
        return src.read(1)

def load_vector(file_path):
    return gpd.read_file(file_path)

# Load final normalized raster datasets from full path
wind_speed = load_raster("D:/Green-Infrastructure-
Biodiversity/data/processed/MCDM/Normalized_Cleaned/WindSpeed.tif")
depth = load_raster("D:/Green-Infrastructure-
Biodiversity/data/processed/MCDM/Normalized_Cleaned/SeabedDepth.tif")
slope = load_raster("D:/Green-Infrastructure-
Biodiversity/data/processed/MCDM/Normalized_Cleaned/Slope.tif")
lcoe = load_raster("D:/Green-Infrastructure-
Biodiversity/data/processed/MCDM/Normalized_Cleaned/LCOE.tif")
firm_activity = load_raster("D:/Green-Infrastructure-
Biodiversity/data/processed/MCDM/Normalized_Cleaned/FirmActivity.tif")
dist_grid = load_raster("D:/Green-Infrastructure-
Biodiversity/data/processed/MCDM/Normalized_Cleaned/DistToGrid.tif")
dist_eco = load_raster("D:/Green-Infrastructure-
Biodiversity/data/processed/MCDM/Normalized_Cleaned/DistToEcoImportantAreas.tif")


# Define final scenario weights (directly derived from Wang et al. 2022 crisp weights and adjusted multipliers)
criteria = {
    'Wind Speed': {'Balanced': 0.141, 'Eco+Social': 0.1173, 'Economic+Construction': 0.1649},
    'Ocean Depth': {'Balanced': 0.1231, 'Eco+Social': 0.1152, 'Economic+Construction': 0.1319},
    'Seabed Slope': {'Balanced': 0.137, 'Eco+Social': 0.1283, 'Economic+Construction': 0.1468},
    'Distance to Grid': {'Balanced': 0.1271, 'Eco+Social': 0.119, 'Economic+Construction': 0.1362},
```

```
    'Distance to Ecological Sensitive Areas': {'Balanced': 0.1172, 'Eco+Social': 0.1829,
'Economic+Construction': 0.0571},
    'LCOE': {'Balanced': 0.2075, 'Eco+Social': 0.1079, 'Economic+Construction': 0.2628},
    'Firm Activity': {'Balanced': 0.147, 'Eco+Social': 0.2294, 'Economic+Construction': 0.1003}
}

# Weighted Linear Combination (WLC) ranking function
def wlc_ranking(scenario_weights, raster_data):
    score = np.zeros_like(raster_data['Wind Speed'])
    for criterion, weight in scenario_weights.items():
        print(f"{criterion} shape: {raster_data[criterion].shape}")
        score += raster_data[criterion] * weight
    return rankdata(-score, method='dense').reshape(raster_data['Wind Speed'].shape)

# Prepare raster inputs
data_layers = {
    'Wind Speed': wind_speed,
    'Ocean Depth': depth,
    'Seabed Slope': slope,
    'Distance to Grid': dist_grid,
    'Distance to Ecological Sensitive Areas': dist_eco,
    'LCOE': lcoe,
    'Firm Activity': firm_activity
}

# Compute rankings per scenario
rankings = {scenario: wlc_ranking({k: v[scenario] for k, v in criteria.items()}, data_layers)
            for scenario in ['Balanced', 'Eco+Social', 'Economic+Construction']}

# Display results
import matplotlib.pyplot as plt
import geopandas as gpd

# Load Natural Earth coastline (built-in with geopandas) to better visualize the results
coastline = gpd.read_file("D:/Green-Infrastructure-
Biodiversity/docs/Ranking_Maps/ne_110m_admin_0_countries.shp")


# Filter for China or nearby countries
china = coastline[coastline['ADMIN'] == 'China']

# Match CRS from any of your rasters
with rasterio.open("D:/Green-Infrastructure-
Biodiversity/data/processed/MCDM/Normalized_Cleaned/WindSpeed.tif") as src:
    raster_crs = src.crs
```

```
# Reproject the vector boundary to match the raster CRS
china_proj = china.to_crs(raster_crs)

# Plotting the rankings
import rasterio

with rasterio.open("D:/Green-Infrastructure-
Biodiversity/data/processed/MCDM/Normalized_Cleaned/WindSpeed.tif") as src:
    transform = src.transform
    width = src.width
    height = src.height
    extent = [
        transform[2],                  # xmin
        transform[2] + width * transform[0],  # xmax
        transform[5] + height * transform[4], # ymin
        transform[5]                   # ymax
    ]


for scenario, ranking in rankings.items():
    ###print(f"Ranking - {scenario}")
    #plt.imshow(ranking, cmap='viridis')
    #plt.colorbar()
    #china_proj.boundary.plot(ax=plt.gca(), edgecolor='black', linewidth=1)  # add coastline
    #plt.title(f"Ranking Map - {scenario}", fontsize=16)
    ###plt.show()
    ranking_clean = np.where(np.isfinite(ranking), ranking, np.nan)

    fig, ax = plt.subplots(figsize=(10, 8))
    img = ax.imshow(ranking_clean, cmap="Oranges_r", extent=extent)
    china_proj.boundary.plot(ax=ax, edgecolor='black', linewidth=1)

    ax.set_title(f"Ranking Map - {scenario}", fontsize=14)
    ax.set_xticks([]); ax.set_yticks([])  # Clean axis
    plt.colorbar(img, ax=ax, label='Rank')

    plt.savefig(f"D:/Green-Infrastructure-Biodiversity/docs/Ranking_Maps/Ranking_{scenario}.png", dpi=300)
    plt.show()
    plt.close(fig)


# Visualization: weight comparison heatmap
weight_df = pd.DataFrame(criteria)
sns.heatmap(weight_df, annot=True, cmap="YlGnBu")
plt.title("Criteria Weights Across Scenarios",fontsize=14)
```

```
plt.ylabel("Criteria", fontsize=12)
plt.xlabel("Scenario", fontsize=12)
plt.xticks(fontsize = 11, rotation=45)
plt.yticks(fontsize = 11, rotation=0)
plt.tight_layout()
plt.show()
```