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GEOSPATIAL, STATISTICAL APPROACH FOR MULTI-CRITERIA ANALYSIS OF RENEWABLE ENERGY POTENTIAL: A CASE STUDY ON JAPAN'S ONSHORE WIND

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ABSTRACT

A new geospatial multi-criteria decision analysis method with spatial regression was proposed and implemented to identify Japan's high-quality onshore wind energy potential in 2030. After identifying the economic potential of grid-connected onshore wind with a GIS-based multicriteria method, logistic regression and Conditional Autoregressive (CAR) regression was used to create a predictive model of development probability and evaluated with ROC curve. Other than economic costs, the model showed other physical, environmental, social factors, and spatial heterogeneity are incorporated to rank the overall quality of potential. The results also showed far more high-quality onshore wind potential exists in Japan than the 10 GW target in 2030.

Keywords: renewable energy, geospatial multi-criteria decision analysis, spatial regression, environment and climate change, capacity expansion planning, Asia

NONMENCLATURE

Abbreviations

LCOE	Levelized Cost of Electricity
POAs	Project Opportunity Areas

1. INTRODUCTION

Under the Paris Agreement to address climate change, all signatory countries are to submit long-term national strategies to reduce greenhouse gas (GHG) emissions by 2050. The development of renewable energy (RE) resources, such as wind and solar power, is one of the central pillars of the national strategies. Integrating RE into national energy planning poses difficulties as follows. First, the geospatial distribution of RE resources are typically uneven, therefore frequently requiring the construction and/or expansion of transmission lines. Second, the temporal variability of RE output constraints the grid integration of RE. It is, therefore, essential to identify the potential of RE resources with sufficient geospatial resolution.

Although the economic costs of RE are critically important for energy planning, other criteria, such as environmental, social, and political criteria, are also accounted for in the decision-making process and realization of RE potential. A wide range of multi-criteria decision analysis (MCDA) has been developed to address the problem. However, current MCDA methods for RE planning do not use empirical data of past RE development to identify the relative importance of various criteria.

This study proposes a new MCDA method with geospatial regression to identify the relative importance of various criteria and integrate them in estimating the overall quality of candidate sites, using Japan's onshore wind development as a case study.

2. METHODS

2.1 Identification of POAs, calculation of the features of each POA, and creation of LCOE curve

First, we employed the geospatial multi-criteria analysis model (MapRE) to identify the economic potential of grid-connected onshore wind in Japan (detailed methods are described in [1], [2]). We identified high-quality project opportunity areas for onshore wind power in Japan by applying industry standard exclusion criteria (summarized in Table 1) using a combination of global- and country-specific

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datasets, which can be categorized into physical, socio-economic, technical, and environmental. We then divided the identified suitable areas into 5 × 5 km spatial grids, called "Project Opportunity Areas (POAs)". Finally, we estimated site selection criteria values for each project opportunity area, including levelized costs of electricity (LCOE). We calculated current and future LCOE in 2030 using future cost projection to identify future economic investment opportunity.

Table 1. Exclusion criteria

Criteria	Exclusion threshold/category
Average wind speed	Less than 5 m/s
Population density	More than 500 person /km2
Distance from:	
residential areas	Less than 500 m
road and rails	Less than 500 m
water areas	Less than 500 m
protected areas	Less than 500 m
Land-use category by Geographical Survey Institute	Ricepaddy, protected forest, urban and built-up area, roads, rails, other use, river, lake, ocean, golf course

2.2 Statistical analysis for estimating influential factors

Next, we conducted statistical analysis to examine which factors are significantly associated with the development of the POAs, using the POAs and existing and planned wind farms. We implemented logistic regression. Because the results showed spatial autocorrelation in the regression residuals, which leads to incorrect estimates of coefficients, we then implemented Conditional Autoregressive (CAR) spatial regression to account for first-order spatial effect, leading to smaller spatial autocorrelation and less unbiased estimate of coefficients of regressions.

2.2.1 Training set and test set

We used existing wind farms as of 2017 and all POAs as a training set to estimate coefficients of the model and make inferences. Then, we used planned wind farms and POAs, after eliminating already developed POAs, to evaluate the predictive performance of the models, true positive rate and false positive rate of the regression models.

2.2.2 Dependent variable

Dependent variable $\mathrm{Y}=1$ if POA is developed, and $\mathrm{Y}=0$ otherwise. We coded the development of each POA as follows. Because we have the coordinates of each turbine, we coded $\mathrm{Y}=1$ if POA is within 2 km distance of at least one turbine. On the other hand, since we have only the centroid of planned wind farms, we coded $\mathrm{Y}=1$ if POA is within 5 km distance of the centroid of at least one planned wind farm.

2.2.3 Independent variables

Based on literature reviews and interviews of industrial experts in Japan, we identified the following key variables which potentially affect the investment decision of wind farms: distance to road whose width is wider than 5.5m; distance to high voltage transmission line whose voltage is higher than 7 kV; distance to large ports; distance to residential areas; distance to legally protected areas; distance to cities whose population is greater than 100,000; elevation; slope; and balancing authority. These distances and the mean values were computed for each POA.

2.3 Ranking high quality POAs in 2030

Using the prediction model, we ranked the POAs whose LCOE is lower than the grid electricity costs in terms of overall quality in 2030.

3. RESULTS AND DISCUSSION

3.1 Identification of POAs, calculation of the features of each POA, and creation of LCOE curve

After applying exclusion criteria, we created 9,749 POAs. Then, we calculated site selection criteria values of each POA. Table 2 summarizes the descriptive statistics.

Table 2. Site selection criteria values of POAs

Variable	Mean (SD)	Unit
Generation LCOE		
2017	116 (18)	USD/MWh
2030	72 (11)	USD/MWh
Total LCOE		
2017	133 (25)	USD/MWh
2030	86 (19)	USD/MWh
Distance to:		
Road	0.95 (5.57)	km
Transmission line	6.63 (13.93)	km
Port	41.30 (23.67)	km
Major city	38.71 (36.11)	km
Residence	2.51 (5.47)	km
Protected area	15.73 (14.58)	km
Mean elevation	446 (338)	m
Mean slope	18 (7)	degree
Mean population density	0.45 (5.51)	Person/km2

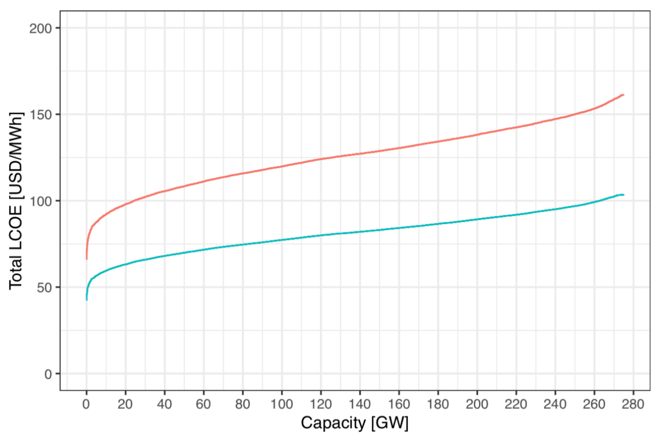

Fig 1 Total Levelized Cost of Electricity of onshore wind power in 2017 (red) and 2030 (blue)

Using the total LCOE values of 9,749, the total LCOE curves in 2017 (red) and 2030 (blue) were created as Fig. 1. Although there is only 2.5 GW capacity below the median costs of grid electricity in FY 2018 (83.6 USD/MWh), the cost reduction increases the capacity below the level of the grid electricity cost to 158 GW in 2030. As stated in the introduction, however, factors other than economic costs also affect the feasibility of the project costs and must be integrated into the energy planning decision-making process.

3.2 Statistical analysis for estimating influential factors and ranking high quality POAs

Of the vast economic capacity of onshore wind capacity in 2030, we ranked relative overall quality of the capacity incorporating the different factors in addition to economic costs, by creating a predictive model of investment using the past investment decisions (i.e. training data). Table 3 shows the mean coefficient and 95% confidence interval of logistic regression and the posterior median coefficient and 95% Bayes credible interval of CAR regression. Generation LCOE, distances to wide roads, major ports, residences, and mean slope showed significant negative correlation with the development of POAs. Distance to major cities and mean elevation showed positive correlation with POA development. Positive and significant sigma 2 represent positive spatial autocorrelation of errors, which implies spatial heterogeneity exist and are controlled in estimating coefficients in CAR regression model. Also, Moran's I statistic of CAR regression residuals greatly decreased compared with that of logistic regression. In addition to economic costs (i.e. generation LCOE), there are numerous factors that could affect investment decisions. Distance to high-voltage transmission lines did not significantly correlate with POA development.

The predictive performance of two models for test data was evaluated by ROC curves in Fig 2. ROC curves of CAR regression outperform that of logistic regression by a significant amount near the left axis. In other words, the true positive rate conditional upon false positive rate of CAR regression was higher than that of logistic regression. For example, conditional upon the false positive rate is 0.01, the true positive rate of CAR regression is 0.27, while that of logistic regression is 0.03. The results indicated that the predictive performance of the CAR regression is greatly improved compared with the logistic information. Therefore, we used the CAR regression model in later sections to integrate various siting criteria values.

The results indicate that economic costs, which is represented by generation LCOE, is only one part of the predictive factors.

Table 3. Regression results

	Logistic regression	CAR regression (spatial regression)
Variable	Coefficient, mean (95% confidence interval)	Coefficient, posterior median (95% Bayes credible interval)
Gen LCOE	-0.0307 (-0.0365 to -0.0249)	-0.0135 (-0.0215 to -0.0060)
Distance to:		
Road	-0.3172 (-0.6551 to -0.1194)	-0.4181 (-0.6368 to -0.1864)
Transmission line	0.0063 (-0.0013 to 0.0134)	0.0064 (-0.0170 to 0.0284)
Port	-0.0101 (-0.0155 to -0.0048)	-0.0181 (-0.0311 to -0.0047)
Major city	0.0033 (0.0008 to 0.0057)	0.0326 (0.0210 to 0.0445)
Residence	-0.0002 (-0.0004 to -0.0001)	-0.0002 (-0.0004 to -0.0001)
Protected area	0.0000 (-0.0000 to 0.0000)	0.0000 (-0.0000 to 0.0000)
Mean elevation	-0.0003 (-0.0009 to 0.0002)	0.0020 (0.0010 to 0.0031)
Mean slope	-0.0544 (-0.0737 to -0.0351)	-0.0748 (-0.1063 to -0.0445)
Utility	controlled	controlled
Tau2	-	2.8398 (2.2285 to 3.5908)
Sigma2	-	0.0105 (0.0032 to 0.0332)
Moran's I of residuals	0.555	0.221

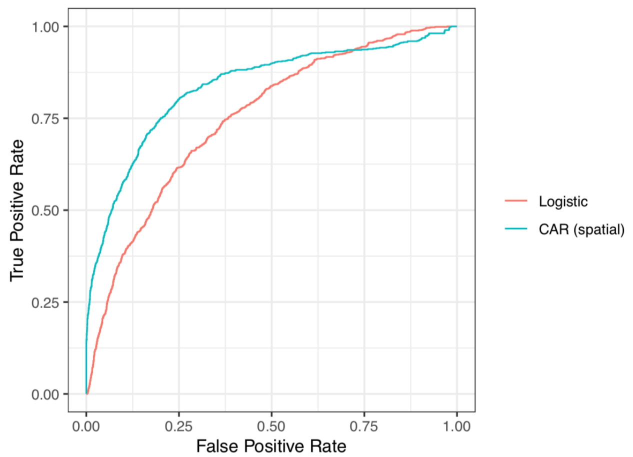

Fig 2 ROC curves of Logistic regression and CAR regression

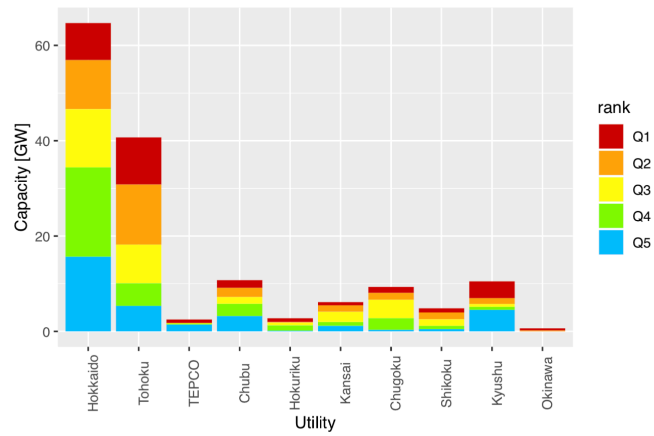

Fig 4 Quantity and overall quality of wind energy potential cheaper than the grid electricity cost (83.6 USD/kWh) in 2030 by 10 balancing areas (utilities)

3.3 Ranking high overall quality wind power potential in 2030

Using POAs' criteria values in 2030 and the estimated CAR regression model, we evaluated overall quality of wind energy potential with lower LCOE than the grid electricity cost (83.6 USD/kWh). Because the Japanese government plans to discontinue subsidies for onshore wind power, currently provided under the Feed in Tariff program, onshore wind power needs to be at least cost-competitive with the grid electricity cost.

We can further incorporate information other than the LCOE by using predicted probability by CAR regression. We ordered the predicted probability of such POAs from highest to lowest and put them in five 20% bins from Q1 (highest probability) to Q5 (lowest probability).

Out of 153 GW, total capacity of Q1 (i.e. top 20% probability) is 28 GW. Although Hokkaido and Tohoku have 65 GW and 41 GW, respectively, Q1 in these areas are 7.8 GW and 9.9 GW. Compared with the current installation of wind power (as of December 2018), which is 3.6 GW, and the 2030 target, which is 10 GW, there is much more available wind potential with the highest overall quality and lower costs than the grid electricity costs.

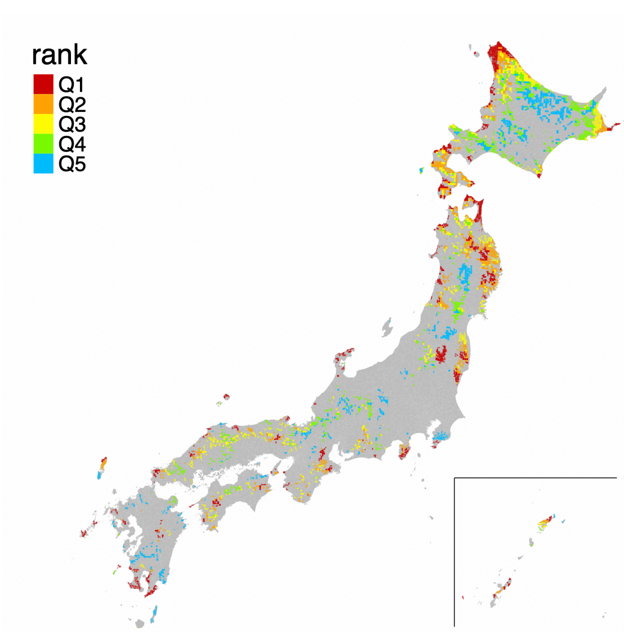

Fig 3 Geographic distribution and its overall quality of wind energy potential cheaper than the grid electricity cost (83.6 USD/kWh) in 2030

4. CONCLUSION

A new geospatial MCDA method using spatial regression with past investment data was proposed and implemented to identify Japan's high-quality onshore wind energy potential in 2030. In addition to economic costs, other physical, environmental, and social factors were incorporated to rank the overall quality of potential. There exists far more high-quality onshore wind potential in Japan than the 2030 target.

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