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Location determinants of industrial solar photovoltaics and onshore wind turbines in the EU

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ABSTRACT

The transition to renewable energy sources, particularly wind turbines and solar photovoltaics, is critical to achieving a climate-neutral European Union. However, challenges in deployment arise related to land conflicts, aesthetics, regulatory barriers and others. While studies have indicated optimal locations, their actual location and associated location determinants remain unknown. This study addresses this gap, with contributions in three key areas. Firstly, it presents the most recent and coherent spatial dataset of onshore wind turbines (118,238) and industrial solar photovoltaics (670 km^2) in the European Union, extracted from Open Street Map. The results present an 8.5-fold and 2.5-fold increase in onshore wind turbines and solar photovoltaics, respectively, compared to similar results from 2020. Secondly, the study provides two models to understand the significance, associated relationship, and strength of a wide range of variables as location determinants. It identifies 16 significant predictors for onshore wind turbines, and 13 for solar PV, uncovering previously unconsidered predictors in optimal placement studies. A 50-fold cross-validation concluded the robustness of both models, allowing for the development of probability maps that illustrate the future expansion potential in the European Union. The regions with the highest wind turbine potential include Denmark, Ireland, the Netherlands, Belgium, northern Germany and France. For solar PV, areas with significant potential are found in the Netherlands, Germany, flat regions in Italy, southern and central Spain, Poland, the Czech Republic, and Hungary.

1. Introduction

The European Union (EU) aims to reduce net emissions by at least 55 % by 2030 and reach climate neutrality by 2050. To realise these targets, the renewable energy (RE) transition is considered a cornerstone [1]. As of 2021, renewable sources comprised 22 % of the total energy consumption, to which wind power (13 %) and solar photovoltaics (6 %) are the largest contributors [2]. In March 2023, the EU, comprised of 27 member states, agreed on stronger legislation, aiming to reach 45 % RE by 2030 [3]. This is acknowledged as a difficult yet achievable target. Its realisation hinges on the European Union undergoing a significant transformation of its energy system throughout the current decade [1,4]. While the EU sets overarching targets and frameworks for RE policies, including through directives and regulations, member states have the autonomy to establish their national targets and develop strategies to meet them in alignment with EU directives.

The transition to RE sources does not come without concerns. Their installation may conflict with existing land uses amid a growing demand for land across various sectors. Additionally, their impact on landscape aesthetics, ecosystems and biodiversity, food production capacity, and cultural values are widely discussed [5]. Consequently, it is in the interest of land use planners to conduct siting assessments and choose optimal locations.

This study contributes to research, policy-making and industry guidance in three areas. Firstly, it presents the most recent and complete spatial dataset of onshore wind turbines and solar PV for the EU. By providing precise location data for each installation, this dataset goes beyond merely displaying aggregated power capacity levels [6]. It allows for the visualisation of exact RE infrastructure locations, highlighting achievements in RE deployment and enabling the identification of remaining gaps. Additionally, the dataset can support analyses at various geographical scales, from continental to local levels.

Secondly, the study introduces a novel modelling approach that integrates six categories —meteorological, orographic, infrastructure, socioeconomic, environmental and policy — to analyse what factors drive the placement of wind turbines and solar PV systems. By quantifying the association of these variables with the placement of RE infrastructure,

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Nomenclature

Abbreviations

AUC	Area Under the Curve
EU	European Union
GDP	Gross Domestic Product
RE	Renewable Energy
Solar PV	Solar Photovoltaics
VIF	Variance Inflation Factor

Notations/Symbols

P	Probability of a location with a wind turbine or solar PV [0 or 1]
Y	Linear predictor
$x_1, x_2, \ldots, x_n$	Explanatory variables
$\beta_1, \beta_2, \ldots, \beta_n$	Coefficient of explanatory variable
β_0	Constant

the study highlights the factors influencing their locations. This approach identifies significant determinants, associated relationship, and their strengths. Research has primarily concentrated on identifying ideal sites by considering meteorological, orographic, and infrastructure factors [7–9]. However, the actual placement of onshore wind turbines or solar PV is likely to differ from these optimal locations, particularly considering the expected influence of socioeconomic, environmental, and policy aspects [10–12]. The influence of these factors on RE placement has thus far been theoretical. Establishing quantified relationships between these factors and RE placement is crucial for developing practical strategies for RE project planning. Not considering important factors may result in recommendations that do not reflect actual influencing factors and thus hinder the successful implementation of RE projects at the pace required to achieve RE deployment targets.

Thirdly, the validated model generates probability maps illustrating onshore wind and solar PV deployment potential across the EU. When high-probability areas are considered alongside regions of high potential, it reveals untapped opportunities for deployment and guides the selection of accessible locations for RE infrastructure. Additionally, identifying factors contributing to deployment challenges enables targeted interventions and policy adjustments to overcome barriers to RE expansion.

Overall, this study thus contributes to advancing knowledge regarding RE deployment dynamics. By bridging the gap and quantifying relationships among a broad range of predictors that were previously only theorised, this research can facilitate informed decision-making.

2. Review of location determinants for onshore wind turbines and solar PV

To understand the location dynamics underlying onshore wind and solar PV locations comprehensively, six variable categories are considered: meteorological, orographic, environmental, infrastructure, socioeconomic, and policy [12,13,16]. The theoretical relations found in the literature informed the selection of explanatory variables in this study. The categories and their variables are following:

Meteorological: Within this category, variables are distinct for both RE sources. Onshore wind turbines were found to be positively associated with wind power density, air density, and wind speed [10,11,13]. In the context of solar PV installations, an ample influx of solar radiation fuels energy generation [9,14,15]. Yet, more subtle factors such as humidity and air temperature can negatively affect the energy potential, possibly reducing the likelihood of installation occurrence [16,17]. Elevation remains subject to scholarly debate regarding its influence on solar PV placement. Moreover, the variability of wind speed and solar radiation is of importance for local power generation capacity which could serve as a location determinant. However, the variability data is only available for certain points but not on the EU scale needed for this study [18,19]. The meteorological wind speed and solar irradiation data used, consider factors that cause this variability. The wind speed data from Global Wind Atlas accounts for flow models for orography, roughness, and roughness change effects [20]. The solar radiation data accounts for the effects of altitude, concentration of aerosols, water vapour content, ozone, the attenuation effect of clouds and terrain shading effects [21].

Orographic: Within this category, variables exclusively pertain to wind or solar installations. Onshore wind turbines are frequently placed in complex terrain. Hilly and mountainous locations exhibit favourable wind resources with localised speed increases over ridges or passages. However, challenges can arise as topography introduces turbulence and channelling effects, potentially resulting in turbines failing to meet expected performance standards for both power production and fatigue life [22,23]. Additionally, steeper slopes exhibit a detrimental impact on wind turbine distribution [10,11]. Elevated locations might offer heightened solar radiation yet might pose accessibility challenges [16,22,23].

Environment: Both solar PV and onshore wind installations share common variables. The effect of agricultural land on the placement of wind turbines is debated, as they can alter CO_2, moisture, and heat exchange with crops [24]. However, dual land use can enhance land value and increase farmers' incomes. When evaluating the potential for both wind and solar energy, it is crucial to consider irrigation requirements and aspects related to suitability for farming, such as ease of maintenance around turbines or under solar panels, as they can influence land productivity [27–29]. While pursuing both RE and food production is increasingly common, the potential drawbacks on crop yield might pose hesitance among farmers pursuing dual-land utilisation [5,24,25]. Regions covered in forest, wetlands, as well as snow and ice are found non-suitable for both RE installations [5,14,26]. Non-forested natural landscapes were also included in the assessment, broadening the scope of land covers considered [14,26,27]. Protected sites do not a priori constrain wind turbine development [28] but were found to be a highly negatively influential factor in RE placement [10,11,29]. The roughness associated with different land cover types directly influences the behaviour of wind and sunlight, impacting the performance and efficiency of RE installations. Therefore, roughness effects are implicitly included in the variables when considering land cover.

Infrastructure: The factors of proximity to airports and natural hazard risks are included for onshore wind turbine siting. The potential interference with radar signals for air traffic and the implications for secure and economically viable operations underscore the negative impact these factors might have [10,11,30]. For both wind and solar installations, the proximity to the grid and proximity to road infrastructure emerge as crucial considerations. These connections are indispensable for both electricity transmission and the cost-efficient execution of installation and maintenance procedures [10,11,15].

Socioeconomic: Within this category, it is expected that high cropland productivity and land rent will negatively affect the allocation of both wind turbines and solar PV [17,24,25]. In contrast, Gross Domestic Product (GDP) might positively affect RE deployment through higher investment means towards the energy transition [12]. Unemployment is associated with different ex-ante and ex-post RE deployment effects. RE is often located in economically deprived areas with low landscape value and a population that lacks the resources to resist its deployment [31]. Despite this, RE installations have the potential to bring economic opportunities to these regions, possibly leading to an improved standard of living. However, advanced production and technical expertise requirements may limit placement in some low-income areas [10,12]. Furthermore, oil, gas, and coal consumption could influence RE installations' placement, as highlighted by Filimonova [32], who observed a negative relationship between non-renewable energy consumption and RE consumption.

Policy: The variables under consideration include fossil fuel subsidies and RE subsidies, as they can affect consumption prices and deployment priorities, and thus fuel competitiveness and demand [12,33,34]. In addition, process-related barriers, for example, site selection, electricity production license obtainment, administrative authorisation, grid connection permit, and corporate legal-fiscal issues, were identified as key culprits for RE underachievement [12]. The analysis also extends to a country's net-zero target, examining whether a higher target is associated with an already high share of RE installations [35].

3. Materials and methods

3.1. Overview

This study focuses on the EU due to the policy relevance of the transition towards RE sources and the high data availability. Data on onshore wind turbines and industrial-scale PV installations within the EU were collected and then analysed against the location determinants using a logistic regression analysis. The locations considered in this regression analysis include sites with and without onshore wind turbines and solar PV installations, respectively, which serve as dependent variables. The independent variables are selected based on the literature review presented in section two, which are collected as raster data or transformed into raster maps. Subsequently, the results of the logistic regressions were used to calculate the probability of wind turbines and solar PV placement for the surface area of the EU.

3.2. Locations of wind turbines and solar PV installations

OpenStreetMap (OSM) was used to collect the most recent locations of wind turbines and solar PV installations. OSM follows a geospatial data structure where points are referred to as nodes, lines as ways, and polygons as closed ways. Tags are used to provide additional information about the objects.

To extract the data for each EU country, the Overpass Turbo API wrapper was accessed through a Python script, which applies key/value pairs to extract wind turbines and solar PV. The script draws on the methodology established by Dunnett [36] in a previous study. The resulting GeoJSON file contains a series of nodes and ways, delimiting the parameters of the items mapped and classified under the pairs of tags and keys. Next, the data was polygonised, resulting in point data for wind turbines and polygons for solar PV.

For wind turbines and solar PV, those situated in urban areas and on water were excluded. This exclusion is justified as the study focuses on industrial-scale installations and onshore wind turbines, which are expected to exhibit different location determinants and trade-offs with other land uses, biodiversity, and landscape aesthetics. To do so, a binary raster layer was created based on Copernicus Global Land Cover 2019 [37], and turbine points and PV polygons falling in urban and water areas were discarded. For solar PV, only surface areas larger than 100 m^2 were represented, omitting installations for private use.

Subsequently, the findings were compared to the results of Dunnett and colleagues [36], who created the first comprehensive global dataset for wind and solar PV locations using OSM data in 2020. Therefore, the study region of the EU was selected from their data, filtering out urban and water areas to ensure comparability.

Table 1
Selected variables for explaining the location of onshore wind turbines and solar PV.

	Variable	Hypothesis Wind	Hypothesis Solar	Parameter	Dataset Source	Data Format, year, resolution
Meteor-ological	Wind speed	+	NA	m/s at 100 m	[20]	Raster, 2022, 150 m
	Power density	+	NA	W/m^2 at 100 m	[20]	Raster, 2022, 150 m
	Air density	+	NA	kg/m^3 at 100 m	[20]	Raster, 2022, 150 m
	Solar Radiation	NA	+	kW/m^2	[21]	Raster, 1994–2018, 250 m
	Humidity	NA	–	g H_2O/Kg air	[38]	Raster, 1984–2021, 5.5 km
	Air Temperature	NA	–	°C	[39]	Raster, 2020, 250 m
Oro-graphic	Slope	–	o	%	[40]	Raster, 2017, 25 m
	Relative elevation	+	NA		[40]	Raster, 2017, 25 m
	Elevation	o	o	m	[40]	Raster, 2017, 25 m
Environ-mental	Non-forest nature	+	o	Dummy (1/0)	[37]	Raster, 2019, 100 m
	Snow and ice	–	o	Dummy (1/0)	[37]	Raster, 2019, 100 m
	Forest	–	–	Dummy (1/0)	[37]	Raster, 2019, 100 m
	Wetland	–	-	Dummy (1/0)	[37]	Raster, 2019, 100 m
	Protected sites	–	–	Dummy (1/0)	[39,40] [41,42]	Vector, 2021
Infrastructure	Airports	–	o	Within distance of 2500 m	[37]	Raster, 2019, 100 m
	Natural hazard risk	–	o	Composite Index	[43]	Vector, 2021
	Transmission lines	–	–	Distance to feature	[44]	Vector, 2023
	Road networks	–	–	Distance to feature	[45]	Vector, 2018
Socio-economic	Cropland productivity	-	-	US$ per 5 arc-minute grid (2010)	[46]	Raster, 2010, 10 km
	Land rent	–	–	Average land rents in EUR/ha (2013)	[47]	Vector, 2013, NUTS 2
	GDP	+	+	GDP per capita at current market prices (2010–2021)	[48]	Vector, 2021, NUTS 2
	Unemployment	o	o	Unemployment rate (2010–2021)	[49]	Vector, 2021, NUTS 2
	Consumption of oil, gas and coal	–	–	Average of thousand tons of oil equivalent (2012–2021)	[50]	Vector, 2012–2021, NUTS 1
Policy	Fossil fuel subsidies	–	–	Average FFS/GDP (2015/2021)	[51]	Vector, 2020, NUTS 1
	Onshore wind subsidies	+	NA	Onshore wind subsidies per capita normalised by GDP (€/cap, 2018)	[51]	Vector, 2020, NUTS 1
	Solar PV subsidies	NA	+	Solar PV subsidies per capita normalised by GDP (€/cap, 2018)	[51]	Vector, 2020, NUTS 1
	Process barriers	–	–	Composite index	[52]	Vector, 2021, NUTS 1
	Net zero targets	+	+	Composite index	[53]	Vector, 2023, NUTS 1

"Hypothesis Wind" and "Hypothesis Solar" signify the assumed relationship of the variable in siting onshore wind and solar PV installations, with either a positive (+), negative (−), or no (o) influence. NA indicates variables that are not included in a specific analysis.

3.3. Explanatory variables

Spatial data was collected on a wide range of explanatory variables for inclusion in the logistic regression analyses (Table 1). The most updated data was collected to represent the conditions of RE installation growth best. This list is derived from the literature review presented in section two. It does not cover variables that lacked data or were available only at a resolution considered too coarse for the study.

All data was processed to ensure a shared extent, resolution, and projection. For each variable, this resulted in raster maps with a resolution of 250 m and ETRS 1989 LAEA projection. The resolution was chosen to strike a balance between the need for detail, given the substantial size of the study region, and the practical considerations of computational resources. Most raster data had an initial resolution higher than the study resolution of 250 m and was thus upsampled using nearest neighbour resampling. The exceptions were cropland productivity and humidity, which had a coarser resolution and for which bilinear resampling was chosen to increase its resolution.

One reference class had to be excluded to ensure an accurate analysis of land cover classes. Agricultural land was excluded, effectively serving as a reference class for all other land cover classes. Consequently, logistic regression results for non-forest nature, snow and ice, forest, and wetland represent the odds of finding RE on that land cover type against the odds of finding it on agricultural land. The variables process barriers and net-zero targets are composite indicators based on national-level data. Process barriers are assessed through a comprehensive traffic-light evaluation for all countries [54], encompassing barriers such as 1) site selection, i.e. the acquisition of a project site and making it legally suitable, 2) electricity production license obtainment, 3) administrative authorisation, i.e. building permits, environmental permission, 4) grid connection permit, and 5) corporate legal-fiscal, i.e. becoming a member of an association, or liable or exempted for taxation, which is especially burdensome for smaller and decentralised installations. For each criterion, a score between zero (no barrier) and three (severe) was assigned, and subsequently, these values were averaged by country. Net-zero targets are also a composite index of national-level indicators. The Net Zero Tracker [53] ranks the countries along a traffic light system based on 1) a detailed plan, 2) a reporting mechanism, 3) international offset credits and 4) greenhouse gas coverage. The traffic light was translated into points: green = two, orange = one and red = zero. The tracker also offers insights into the level of stringency for implementation, which was utilised to apply weights to the scores assigned. These weights include a law (0.4), policy document (0.3), declaration/pledge (0.2), and proposal (0.1). The average index describes the level of ambition, ranging from the highest score of 0.8 to the lowest of 0. The analysis does not incorporate changes in predictors over time nor introduce predictor weighting, such as considering the concentration of RE installations in a country. This was a deliberate choice not to introduce bias in the analysis.

3.4. Logistic regression analysis

Two balanced samples were created, each containing an equal number of points with and without RE installations for wind turbines and solar PV. A binary raster map was first generated for each type of RE to indicate whether wind turbines and solar PV were present or absent for each pixel. Next, for each type of RE, the raster data was converted into polygons, and this set was reduced to ensure a minimum distance of 1000 m between each point to reduce spatial autocorrelation. The same procedure was repeated for each type of RE, to generate an equal amount of non-PV and non-turbine points, again excluding urban and water areas and with a minimum distance of 1000 m to avoid spatial autocorrelation. The combination of selected locations and non-locations per type of RE thus entails a set of points with an equal number of true and non-true locations for both wind turbines and solar PVs. The values for all variables were retrieved for all points in both balanced samples. The generation of the samples was conducted in ArcGIS Pro 3.0.

Based on the sample, the multicollinearity of the variables was first assessed using the correlation coefficient (r) and the Variance Inflation Factor (VIF). One was removed for each variable pair with a correlation coefficient >0.8. Similarly, all variables with a VIF higher than five were removed from the set of variables. This process led to removing oil, gas, and coal consumption and power density for wind turbines. Following those removals, the remaining variables were re-tested for multicollinearity, and no issues were detected. The same steps were followed to identify the variables for the solar model. The multicollinearity analysis revealed that no variables were correlated, and the VIF for all variables was below five. However, snow and ice were dropped from the analysis, as no point fell on this land cover. Subsequently, the logistic regression analysis was conducted in Stata.

The explanatory power of the logistic regression analysis was assessed using the Area Under the receiver operating Curve (AUC). The AUC ranges from 0.5 to 1, where 0.5 indicates no explanatory power, while 1 indicates perfect prediction. Predictor importance was calculated based on the loss of predictive capacity (measured by the AUC) after omitting one variable at a time. A fifty-fold spatial cross-validation was conducted using only significant explanatory variables. Hence, the dataset was divided into ten equal sets, with seven sets used for training the model and three for validation. This process was repeated fifty times for both models on spatially independent sites, and AUC values were assessed to evaluate the model's performance.

3.5. Projection

The result of the logistic regression was used to create probability surfaces for future locations of wind turbine and solar PV occurrence in the EU based on the current values of explanatory variables and the current-generation RE. Specifically, the probability of finding wind turbines and solar PV installations for each pixel was calculated using the logistic regression formula following Eq. (1).

$$P = 1 \Big/ \left(1 + e^{(-Y)}\right), \text{with } Y = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \ldots + \beta_n * x_n \quad \text{Eq. (1)}$$

where P represents the probability of a location having a wind turbine or solar PV, respectively, with values ranging from 0 to 1. Y is the linear combination of explanatory variables $x_1, x_2, \ldots, x_n$, each multiplied by its respective coefficient $\beta_1, \beta_2, \ldots, \beta_n$, and a constant β_0. Note that probabilities in this analysis represent probabilities in comparison to other pixels and not absolute probabilities of finding a wind turbine or solar PV installation in a pixel at a specific point in time.

4. Results

4.1. Current onshore wind turbines and solar PV installations

The OSM analysis for the EU yielded 122,880 data points representing wind turbines, including 1081 lines denoting larger installations. As a line is represented by several points in all cases, they can be understood as duplicates of the points and are therefore excluded from the analysis. From the total extracted data points, 4642 are situated in urban or water areas, thus leaving 118,238 turbines for further analysis. The geographical distribution indicates that Germany, Spain, and France have the most wind turbines and exceed the collective count of all other countries (Fig. 1a). Conversely, 20 countries have less than 5000 turbines each, illustrating the variation within the EU. When expressed in wind turbine density, the Netherlands and Denmark have densities of 0.23 and 0.13 turbines/km^2, respectively, surpassing those of Germany, Spain, and France, which range from 0.08 to 0.035 turbines/km^2.

The analysis yielded a total of 670 km^2 of solar PV installations in the EU, with large differences between the countries. It shows that most EU

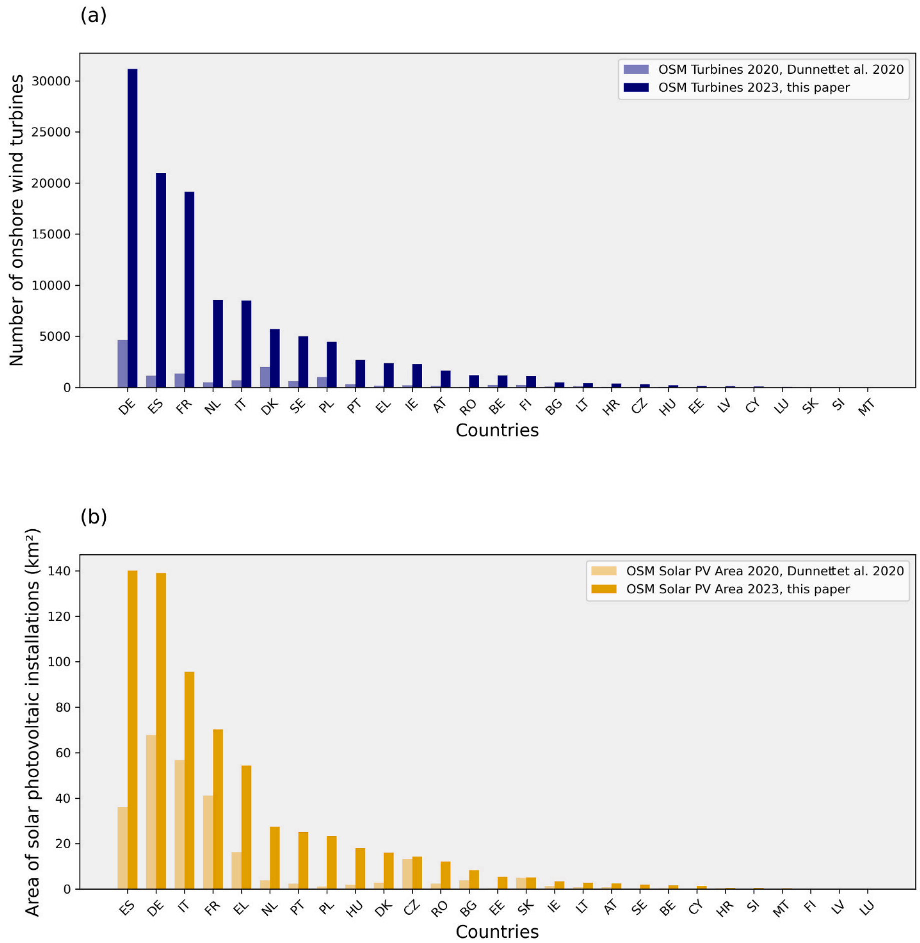

Fig. 1. Comparison of OSM data for 2020–2023 for a) onshore wind turbines and b) solar PV installations.

member states have relatively modest solar PV surface areas within the continental EU, with 19 having less than 20 km^2. In contrast, the top five countries collectively cover a surface area approximately four times greater than the combined PV surface areas of the remaining countries. Spain and Germany emerge as frontrunners in this context, covering approximately 140 km^2 and 139 km^2, respectively (Fig. 1b). Italy, France, and Greece follow closely, with respective surface areas of around 95 km^2, 70 km^2, and 54 km^2 dedicated to industrial solar PV installations. Conversely, Luxembourg, Latvia, Finland, Malta, Slovenia, and Hungary are at the lower end of the ranking, each with industrial solar PV surface areas of less than 0.5 km^2 (Fig. 1b). Relative to the surface area, the highest density of solar PV area can be found in Germany, Italy and the Czech Republic, in descending order.

In this study, both the number of wind turbines and the area covered by solar PV significantly surpass Dunnett's [36] findings, with an 8.5-fold increase for wind and a 2.5-fold increase for solar (Fig. 1). Spain stands out as a country, where the numbers for both wind turbines and solar PV have increased substantially between 2020 and 2023. Moreover, there seems to be a notable trend of higher wind turbine and solar PV installations in Central and Southern European countries compared to Northern European countries. While Germany, Spain, France, Italy, and the Netherlands have experienced significant growth in mapped wind and solar installations in OSM, the Nordic countries, including Sweden, Finland, and Denmark, have comparatively fewer mapped installations for 2020 and 2023.

4.2. Location determinants of onshore wind turbines and solar PV installations

Of the 21 variables used in the logistic regression for onshore wind turbines, 16 predictors show to be of significance ($P < 0.05$) in determining their locations (Table 2). The result column in Table 2 shows that nine predictors exhibit the anticipated associations as indicated in the literature, while 12 predictors demonstrate contrasting relationships. The latter included non-significant associations (null), while significant relations were expected.

Of the 20 variables for solar PV installations, 13 were identified as significant predictors (Table 3). For nine predictors, the findings align with the literature, while 11 oppose the assumed hypothesis. The latter included seven non-significant associations (o), while significant relations were expected.

The logistic regression models explaining the allocation of onshore wind turbines and solar PV installations yielded AUC values of 0.88 and 0.84, respectively. This implies that the performance of both models significantly exceeds random guessing.

Wind speed is the most influential predictor in the wind model, resulting in a notable AUC decrease of 0.100 when removed (Fig. 2a). The remaining predictors show only modest AUC decreases, ranging from 0.005 to 0.001. Conversely, the solar model shows a more nuanced predictor contribution, with solar radiation (0.020) and net zero targets (0.012) as the most important predictors (Fig. 2b). Yet, similar to the wind model, most predictors in the solar model show modest reductions in AUC, ranging from 0.010 to 0.001.

Given the low levels of collinearity, well-validated models, a balanced dataset, and a substantial number of data points, both models

Table 2
Logistic regression results for onshore wind turbines.

Variable	Odds ratio	Standard Error	P-values	Hypothesis	Test result	Result
Wind speed	3.471	0.097	0.000	+	+	Confirm
Relative slevation	3.376	0.361	0.000	+	+	Confirm
Net-zero targets	1.313	0.208	0.086	+	o	Reject
Process barriers	1.219	0.097	0.012	–	+	Reject
Land rent	1.039	0.026	0.122	–	o	Reject
Unemployment	1.027	0.008	0.001	o	+	Reject
Onshore wind subsidies	1.011	0.001	0.000	+	+	Confirm
Natural-hazard risk	1.003	0.014	0.858	–	o	Reject
GDP	1.001	0.001	0.526	+	o	Reject
Distance to roads	1.000	0.000	0.003	–	+	Reject
Fossil fuel subsidies	1.000	0.000	0.001	–	+	Reject
Crop productivity	1.000	0.000	0.000	–	+	Reject
Distance to transmission lines	1.000	0.000	0.000	–	–	Confirm
Elevation	1.000	0.000	0.101	o	o	Confirm
Slope	0.986	0.004	0.001	–	–	Confirm
Non-forest nature	0.539	0.048	0.000	+	–	Reject
Airport	0.404	0.111	0.001	–	–	Confirm
Forest	0.387	0.024	0.000	–	–	Confirm
Wetland	0.380	0.155	0.017	–	–	Confirm
Protected sites	0.273	0.024	0.000	–	–	Confirm
Air density	0.001	0.001	0.000	+	–	Reject
Constant	0.214	0.204	0.106			

In the columns "Hypothesis," denoting the theoretical relation and "Test result", representing the relation observed in the analysis, there is either a positive (+), negative (−), or no (o) relation between onshore wind turbines and the variable. The "Results" column assesses the test outcome against the hypothesis, categorised as either "Confirm" or "Reject".

Table 3
Logistic regression results for solar PV.

Variable	Odds ratio	Standard Error	P-values	Hypothesis	Test result	Result
Solar PV subsidies	11.262	5.176	0.000	+	+	Confirm
Process barriers	2.173	0.542	0.002	–	+	Reject
Non-forest nature	1.079	0.194	0.671	o	o	Confirm
Land rent	1.027	0.059	0.637	–	o	Reject
Unemployment	1.011	0.018	0.529	o	o	Reject
GDP	1.007	0.002	0.001	+	+	Confirm
Solar radiation	1.002	0.000	0.000	+	+	Confirm
Consumption of oil, gas and coal	1.000	0.000	0.000	–	+	Reject
Crop productivity	1.000	0.000	0.274	–	o	Reject
Distance to transmission lines	1.000	0.000	0.000	–	+	Reject
Distance to road	0.999	0.000	0.000	–	–	Confirm
Elevation	0.998	0.000	0.000	o	–	Reject
Air temperature	0.995	0.002	0.002	–	–	Confirm
Slope	0.953	0.016	0.003	o	–	Reject
Wetland	0.854	1.028	0.896	–	o	Reject
Fossil fuel subsidies	0.722	0.285	0.410	–	o	Reject
Forest	0.422	0.054	0.000	–	–	Confirm
Protected sites	0.285	0.062	0.000	–	–	Confirm
Net-zero targets	0.041	0.018	0.000	+	–	Reject
Humidity	0.000	0.004	0.350	–	o	Reject
Constant	0.355	0.225	0.102			

In the columns "Hypothesis", denoting the theoretical relation and "Test result", representing the relation observed in the analysis, there is either a positive (+), negative (−), or no (o) relation between solar PV and the variable. The "Results" column assesses the test outcome against the hypothesis, categorised as either "Confirm" or "Reject".

are grounded in diverse predictors that collectively enhance their predictive accuracy. The marginal reductions in AUC for each predictor indicate that all 16 final wind predictors and all 13 solar PV predictors substantially contribute to the models' predictive performance, distributing the predictive power across multiple predictors.

Fig. 3 illustrates the 50-fold cross-validation for both models. Both generated highly similar results regarding the ROC curve for all folds The consistency is highest for the model explaining the allocation of wind turbines, indicating that the wind model maintains a very stable and reliable performance throughout all iterations (Fig. 3a). The solar PV model's greater variability among the grey curves suggests that its performance is slightly less consistent across different iterations (Fig. 3b). Despite this, both models show high validity and can thus be used to derive predictive probability surfaces.

4.3. Spatial extrapolation

Extrapolation of the model results generated probability surfaces with high variation between and within countries, both for wind turbines and solar PV, as shown in Fig. 4. The areas with the highest wind turbine probabilities (ranging from 80 % to 100 %) are primarily found in Denmark, Ireland, the Netherlands, Belgium, and the northern regions of Germany and France (Fig. 4a). In addition, there are noticeable pockets of high probability in southern France and Portugal, as well as northern Spain, extending inland. These areas are all characterised by relatively high wind speeds, mostly due to their location near the Atlantic Ocean and North Sea. In the EU, approximately 9 % of the total land area exhibits a likelihood higher than 70 % for wind turbine placement. Notable across the EU region is that there is also a significant

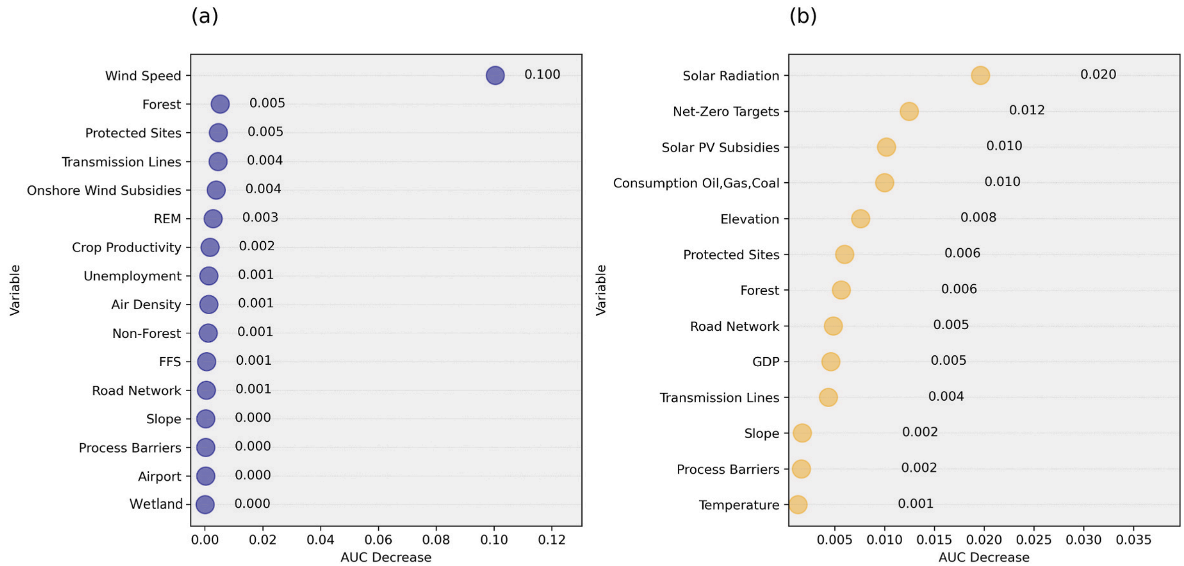

Fig. 2. Predictor importance explaining the occurrence of RE installations measured through the AUC decrease for the a) onshore wind turbine model and b) solar PV model.
*FFS – Fossil Fuel Subsidies, REM – Relative Elevation, GDP – Gross Domestic Product.

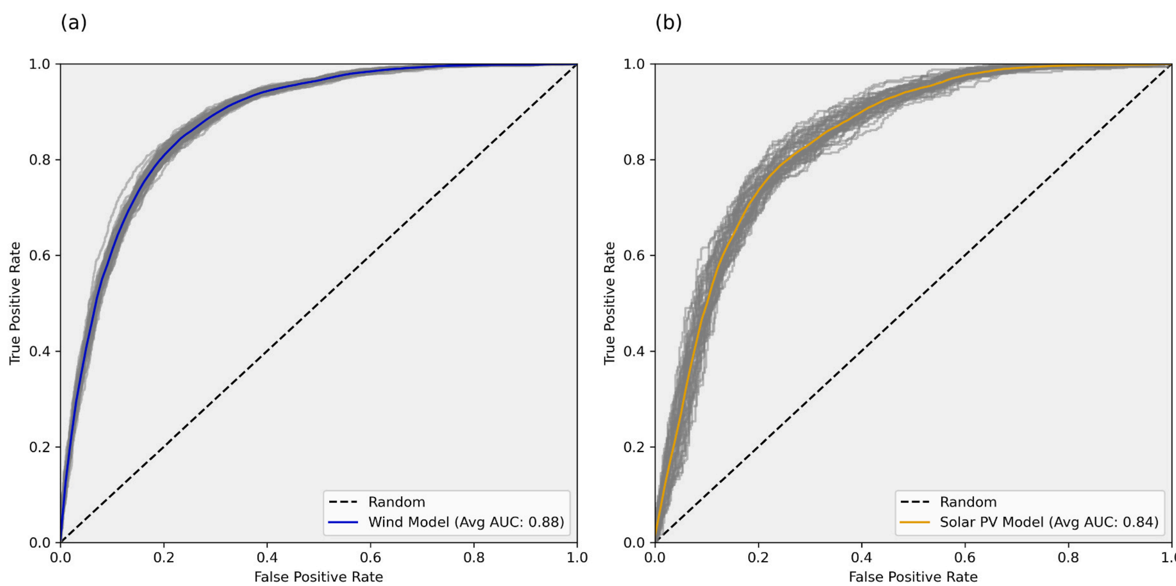

Fig. 3. ROC curves (50-fold spatial cross-validation) for a) wind model and b) solar PV model.

portion of the land surface with very low probabilities, i.e., below 10 %. Areas of low probability are concentrated in central and southern Europe, with the probabilities of wind turbine occurrence below 10 % in large parts of central Spain, northern and central Italy, Greece, Bulgaria and Romania.

For solar PV, areas with the highest probability are concentrated in the Netherlands, Germany, the flat areas in Italy, and southern and central regions in Spain and Poland, as well as the Czech Republic and Hungary (Fig. 4b). Approximately 10 % of the EU's land area has a probability exceeding 70 % for solar PV development. Conversely, areas with relatively low probabilities of finding future solar PV installations are in Scandinavia, the Baltics, and the mountainous regions such as the Alps, the Carpathians, the Dinaric Alps, and others. Consistent with the logistic regression model results, these areas are characterised by unfavourable conditions, especially low incoming solar radiation. As a result of the local variation in topographic conditions, areas with low and high probabilities can occur near each other. Unlike the probability map for wind turbines, the country boundaries are more distinct for solar PV, highlighting the importance of national-scale determinants such as subsidies and net-zero targets.

5. Discussion

5.1. Location determinants of current and future wind turbine installations

The number of onshore wind turbines is tallying up to a total of 118,238, representing an 8.5-fold increase compared to the latest estimates by Dunnett [36] for 2020. This increase cannot be attributed solely to the rapid implementation of RE: In the same timeframe, the EU onshore wind power capacity (in megawatts) increased by 1.2-fold [55, 56]. While a linear relationship between the amount or area of installations and capacity should not be assumed, these figures nonetheless indicate that the mapping approach yielded significantly higher

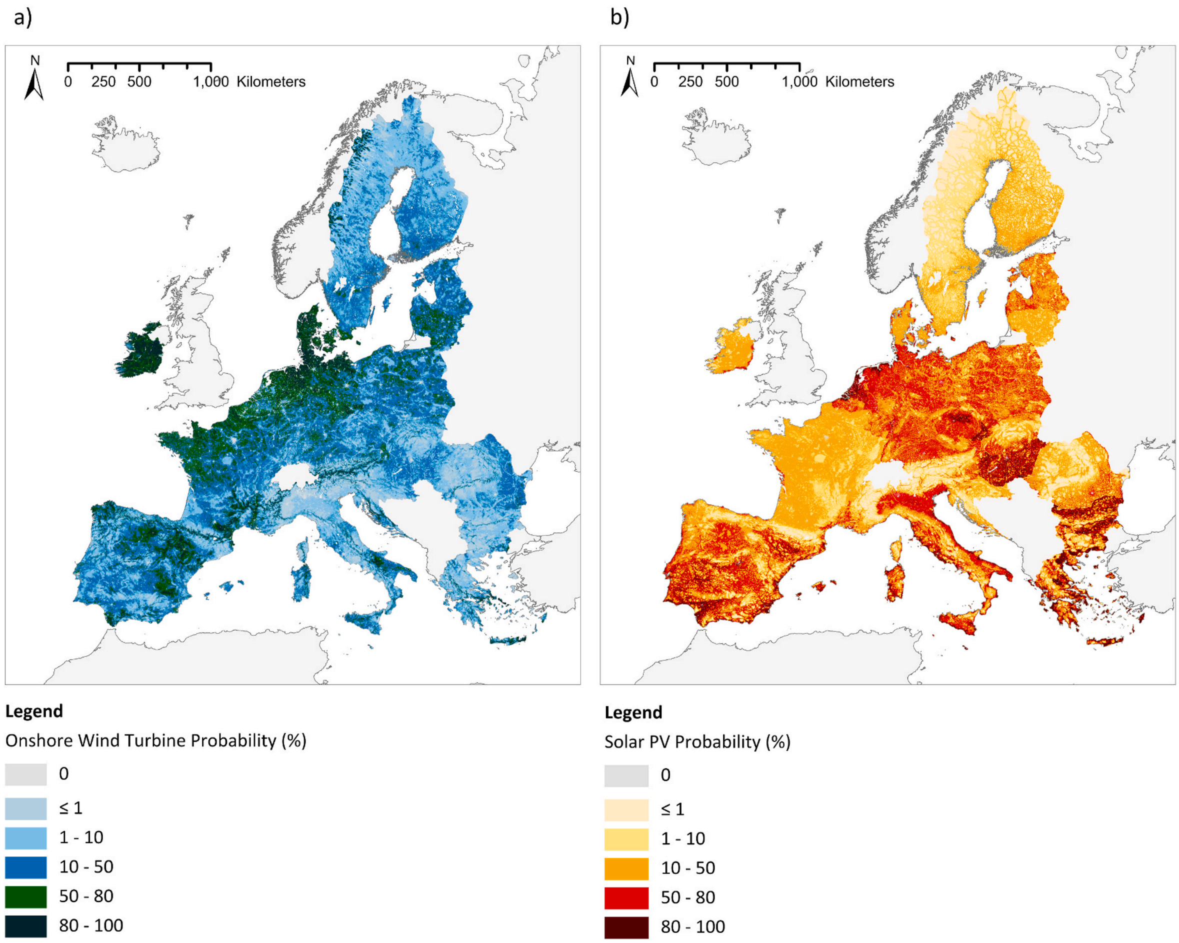

Fig. 4. Future probability surfaces for a) wind turbines and b) solar PV.

numbers of wind turbines, likely due to better coverage in OSM, thus considerably reducing errors of omission.

The study finds 16 predictors that can explain wind turbine placement in the EU. The location of onshore wind turbines is explained mostly by the local wind speed, which aligns with previous studies [11]. Specifically, the probability of turbine occurrence increases drastically within the wind speed range of 4–10 m/s, affirming research showing that wind projects attain financial viability with wind speeds of 7 m/s [10]. Several socioeconomic and biophysical factors add further detail to the probability of turbine occurrence. Notably, relative elevation, which refers to the height relative to the nearby surroundings, emerges as a significant factor. While topography can lead to complex local wind circulation dynamics, the study suggests a positive relationship between relative elevation and turbine placement within the EU. This factor's importance surpasses orographic factors such as elevation and slope commonly considered in optimal placement studies [10,11].

Regarding land cover, the results show that wind turbines are more likely to be situated on agricultural land than other types of land. Moreover, productive agricultural land is associated with more installations. Conversely, and in contrast with hypotheses derived from previous research [10,26] other non-forested land cover types are negatively associated with wind turbines relative to the agricultural land reference class. The association with agricultural land could be the effect of path dependency, where countries with more agricultural land were historically the first to adopt the technology, or the effect of a causal mechanism, in which agricultural land is more suitable from a technical or land use planning perspective. Additionally, landowner preferences might play a role, as dual land use might be employed to generate additional income [25]. The preference for agricultural land as sites for wind turbines may raise challenges for land planners, as agricultural areas are often close to human settlements. Therefore, these locations are likely to cause resistance, for example, due to aesthetic impacts [57]. Protected sites show a highly significant negative association when explaining wind turbine locations. While the Habitat Directive does not, a priori, exclude wind turbine development in or close to Natura 2000 areas, it becomes evident that the assessment and granting procedures significantly influence their placement [28,58].

Onshore wind energy subsidies are positively associated with turbine probability. Contrary to expectations, the same positive association is also found with fossil fuel subsidies. It is unlikely that this relationship is directly causal. Rather, this can result from a continuance of interventionist industrial policies [59]. In other words, countries with a tradition of steering energy provision and industry through fiscal incentives will simultaneously have high fossil fuel and wind energy subsidies.

The study confirms that infrastructure predictors influence turbine placement. Consistent with the literature, there is a slightly negative association with the distance to transmission lines [13]. Also, in line with existing literature, a higher distance to airports is associated with a higher likelihood of turbines, mitigating the interference with radar signals and increasing air traffic safety [10,11,13]. A slight positive influence of distance to roads can be observed, which is against the expectation of lower turbine likelihood when an area is less accessible. Zoning regulations and land use planning policies may influence the spatial distribution of turbines relative to roads.

Lastly, the findings underscore a positive association between unemployment and wind turbine occurrence. This aligns with Boyle's [60] conclusion that regions with higher unemployment rates show a greater tendency for wind turbine installation as they might lack the resources to resist, unlike higher-income households [60,62]. However, this association could also be explained by the characteristics of rural areas — increased wind exposure, socioeconomic disadvantages, lower landscape value and lower population density [31].

5.2. Location determinants of current and future solar PV installations

The analysis yielded a total of 670 km^2 of solar PV in 2023 located in the EU, representing a 2.5-fold increase in solar PV, respectively, compared to the estimates by Dunnett in 2020 [36]. However, solar PV capacity increased only 1.4-fold in the same period [55,56]. This disparity suggests that the expansion of solar PV installations cannot solely be attributed to actual deployment. Rather, improved mapping results are likely driven by better coverage by OSM and improved querying of OSM, which can explain this increase. Better OSM coverage reduces errors in the analysis but also signals an enhancement of data quality when working with open data sources.

The study shows that 13 predictors influence the location of solar PV installations. The top three most influential predictors are incoming solar radiation and solar energy subsidies, both confirming the prior hypothesis, while net-zero targets oppose the initial hypothesis. On the orographic factors, the analysis reveals a negative impact of elevation on the presence of solar PV installations, where existing literature offered mixed insights. While some studies hinted at the potential benefits of high-elevation PV installations [27], other studies assumed a negative influence [9,14,15]. The preference for lower elevations can be attributed to flatter terrain and readily available land requiring minimal levelling and facilitating installation [10,11,19]. The study also confirmed the negative association with higher air temperatures, which were found to decrease the efficiency of solar panels [17].

As for wind turbines, agricultural land emerges as the predominant land cover for solar PV, as all other significant land covers show a lower odds ratio relative to cropland. This indicates the adoption of dual-land practices, wherein farmers integrate RE generation with agricultural activities. The emergence of agrivoltaics, which combines solar PV with crop production, has gained traction in the past years, as reflected in the study findings [61,62]. Additionally, confirming the literature, the results indicate that solar PV installations are unlikely to be in protected areas [29]. Moreover, consistent with the hypothesis, solar PV is less likely to be found in forest areas than in cropland.

Discrepancies emerge between the anticipated impact of various policy predictors and the observed placement of solar PV and wind installations. This can be attributed to the diverse strategies adopted by different countries. For example, Nordic countries like Sweden have set ambitious net-zero targets, relying predominantly on non-solar RE sources [63]. In contrast, countries like the Netherlands lack explicit net-zero targets while excelling in RE installations [53]. Moreover, while RE is necessary to achieve net-zero targets, currently high net-zero targets do not imply an already high deployment, as they are forward-looking in their nature. The legacy effect suggests that past decisions and existing infrastructure may shape the attractiveness of certain countries for RE deployment, even in the presence of ambitious climate targets.

Another discrepancy lies in the positive association between solar PV and oil, gas and coal consumption. Based on the finding of Filimonova [32], the initial hypothesis was that fossil fuel and RE consumption are associated with "inter-fuel competition", implying low levels of co-occurrence. Yet, the analysis shows the opposite, indicating a rather complex and evolving energy landscape in the EU, where both energy sources co-occur. This could reflect the ongoing energy transition where countries utilise fossil fuels and RE sources like solar PV simultaneously. It may also indicate that solar PV is seen as a complementary energy source rather than a direct substitute for fossil fuels. However, with the net-zero targets set by many European countries, including the aim to phase out fossil fuels and scale up RE deployment, this positive association will likely become negative.

Although a report by the European Commission identified process barriers as the primary reason for the underperformance of renewables in the EU [52], this analysis found its positive association with both solar PV and wind turbine occurrence. Notably, Germany stands out as a country with high process barriers and a high share of wind turbines and solar PV. This suggests that the causal relationship between RE and process barriers is reversed: process barriers arise as a response to the growing deployment of RE infrastructure, leading to the implementation of regulatory frameworks. Furthermore, they can also signify untapped potential, as overcoming these barriers may accelerate further deployment.

Regulatory frameworks and zoning policies governing wind and solar development may influence their proximity to roads. Zoning ordinances may restrict the location of wind turbines near residential or sensitive areas due to concerns about noise or visual impacts, leading to placements further away from roads. Conversely, solar PV installations may face fewer zoning restrictions and be more readily permitted in areas closer to existing road infrastructure.

5.3. Limitations

The analysis conducted in this study is intrinsically bound by its focus on utilising spatial predictors. Some of these predictors are unavailable at the necessary resolution or consistency on the EU level. For instance, factors such as variability in power generation, terrain roughness and geological suitability for both onshore wind and solar PV are lacking and could thus not be included. For future studies, it is recommended to consider these actors in case the data becomes available. This is because, for example, in the current dataset, the presence of highly fluctuating wind speeds outside the optimal range for wind turbines might be obscured by averaged wind data that might appear favourable. If found significant, this factor would also impact the probability surfaces, potentially overestimating location probabilities with highly variable wind speeds or solar radiation. Nevertheless, the factors currently included in the analysis demonstrate strong explanatory power, as supported by model validation.

Other aspects, such as resident, farmer, and landowner considerations, might also exert a significant influence on RE placement [29,64,65]. The intricate interplay of these factors shapes the complex decision-making process behind the placement of RE infrastructure. Hence, it is imperative to note that certain drivers and phenomena may not be adequately captured within the scope of European-level spatial data. The not in my backyard (NIMBY) phenomenon, where local communities resist the installation of turbines due to perceived negative impacts, is a prominent example of an influential driver not directly included in spatial information alone. Very local effects that constitute the complex dynamics of the NIMBY phenomenon are visual impact, ownership, information, and participation, as well as age, gender, income and attitude [31,57,60,65].

The spatial extrapolation of our findings is based on relationships determined at the EU level. However, regulations on factors like protected areas or distance to airports may differ from one country to another. As a result, the probability maps generated by the models may not fully account for variations in the enforcement measures at the national level. Future research could explore ways to incorporate country-specific factors into spatial modelling approaches to improve the accuracy of predictions and account for cross-country differences in regulatory frameworks.

The predictor variables were extracted based on the latest available data, reflecting the evident upward trend in wind turbine and solar PV installations. In 2023, Europe reached a peak in installed wind power capacity of 257.1 GW. This reflected a consistent growth pattern from 2010 to 2023, with figures more than doubling over this period [66]. Furthermore, solar PV capacity in the EU steadily expanded, reaching 259.99 GW in 2023, with an additional 32.8 GW added in 2022 alone [67,68].

Considering the dynamic nature of RE technologies and the social, economic, and political contexts in which they are established, it is crucial to note that we selected datasets reflecting the most recent situation. This ensures validity and explanatory power for current-generation RE. Consequently, our results should be interpreted carefully when evaluating historical patterns or estimating future developments.

In response to the surge in deployment, the selection of predictor data was tailored to reflect the most current conditions. This methodology captures the underlying dynamics driving the most recent years of RE deployment in the EU. While the evolution of explanatory factors such as changing infrastructure, regulations, or RE technology should be noted, their impact on the findings is considered minimal. Nonetheless, further research could delve into these phenomena to deepen the comprehension of RE deployment dynamics over time.

Other factors might be misleading in their real-life association with RE deployment and the relationship found in the models. This can be exemplified by the relationship of net-zero targets as a predictor for solar PV locations, which was found to be negative in the study. Although the relationship was validated and thus holds theoretical explanatory power, the real-life relationship is expected to be positive when countries come closer to achieving their targets. By including the negative coefficient in the probability surfaces, the factor might now reduce probabilities on a country level for the countries with high net-zero targets.

Moreover, applying spatial extrapolation based on current data implies that the analysis does not account for potential future changes, such as those arising from climate change or policy shifts. While these factors might alter the determining factors [69,70], the overall patterns of RE placement are likely to remain robust. Infrastructural adjustments, like road development or grid infrastructure expansion, are also plausible, especially with the evolving landscape of RE initiatives, but these changes are expected to be gradual and may not drastically alter the overall spatial distribution. Additionally, bird migration routes are crucial for environmental assessments but could not be incorporated due to EU-level data limitations.

5.4. Implications

The results offer insights that can support evidence-based policy development, especially at the EU level and beyond. As open data quality improves, it underscores the importance of re-extraction to accurately reflect the evolving landscape[39]. Additionally, the significant increase in RE installations suggests that similar trends may be observed in regions beyond the EU, necessitating an updated harmonised extraction at the global level.

The methodology to identify location determinants employed in this study can also be applied in other regions worldwide, utilising the same overarching categories. However, careful consideration should be given to the chosen variables, as the local context and interpretation may present different hypotheses compared to those relationships theorised for the EU.

The wind turbine and solar PV probability maps indicate how likely the placement of this RE infrastructure is to take place in specific locations. This is not equal to the physical potential for RE, and a discrepancy between probability and potential is a sign of opportunities being missed. Ruiz [71] have produced RE potential maps on a country basis. Comparing this to the study results shows that for wind turbines, Spain, Italy, France, Poland, Greece, Romania, and Sweden have a high potential but a relatively low probability. In descending order, solar PV has high potential but relatively low probability in France, Romania, Spain, Poland, Italy, and Germany. These countries exhibit regions representing areas where creating an enabling environment for RE provides low-hanging fruit for the EU energy transition.

Moreover, the probability maps highlight the areas where land conversion is likely to occur under current influencing factors. This information can also help to anticipate the location of land use change and land use conflicts. Therefore, the identified zones for high-potential expansion demand an integrated land-use planning approach. Moreover, it is imperative to extend RE deployment to areas with lower suitability to meet the EU climate objectives. Scenarios could be developed that reflect anticipated variable future predictor changes that could enable RE development in currently low-probability areas.

Considering probabilities of expansion of RE installations can be useful to accurately design future developments that align with sustainable development and conservation goals. The EU Biodiversity Strategy for 2030 sets the target of protecting 30 % of EU land and sea area by 2030, of which one-third is strictly protected [60]. If the observed negative relationship between RE installations and protected sites continues, allocating new protected areas may limit the available land for meeting food and energy demands. Achieving a balance among these competing demands underscores the importance of integrated land use planning. Such planning necessitates aligning the objectives of government organisations, conservation entities, and RE developers to ensure sustainable land allocation that promotes a safe planet and society.

6. Conclusion

First, this study presents the most recent spatial dataset for onshore wind turbines and industrial solar PV in the EU, including 118,238 wind turbines and 670 km^2 solar PV installations, representing a sharp increase compared to Dunnett's previous study [36]. Re-extracting OSM data is thus imperative, as otherwise, analysis based on past extractions cannot reflect the most recent developments.

Second, it provides the first quantified compilation of a wide range of predictors, including meteorological, orographic, location, environmental, socioeconomic and policy aspects, to explain the actual location of wind turbines and solar PV in the EU. For wind, 16 predictors and for solar 13 predictors contribute to the model's explanatory power. This reveals the importance of including the under-represented environmental, socioeconomic and policy factors the placement of RE infrastructure, reducing the barriers that currently skew actual from optimal locations. It stands out that wind speed is the most important predictor for wind turbines, just as solar radiation and solar subsidies are for solar PV. Moreover, agriculture is the land cover that provides the most favourable conditions for RE deployment in the EU. While spatial factors play a crucial role in determining the allocation of wind turbines, capturing local dynamics, such as resident opinions and topography-related wind turbulence, proves challenging at the EU level. Utilising locally applied explanatory models can enhance the understanding in this regard. Moreover, regional studies could shed light on predictors that apply to other regions outside of the EU.

Third, the study provides probability surfaces for the future placement of wind turbine and solar PV sites respectively. From that, regions with a high probability for RE development can be inferred, potentially pointing at regions prone to future land use conflicts. The study also finds discrepancies between regions with supposedly high potential but low probability. Areas with high, untapped wind energy potential are identified in regions across Spain, Italy, France, Poland, Greece, Romania, and Sweden. Regions with significant solar potential are found in France, Romania, Spain, Poland, Italy, and Germany.

While this study aimed to analyse variables and extrapolate probability surfaces based on current explanatory factors, future endeavours could delve into methodologies considering spatiotemporal changes in these factors. This could involve employing dynamic modelling approaches or conducting sensitivity analyses to assess how the model predictors evolve.

CRediT authorship contribution statement

Anna Bessin: Methodology, Data curation, Validation, Formal analysis, Investigation, Writing – original draft, Visualization. **Jordi Serra-Adroer:** Methodology, Investigation, Data curation. **Niels Debonne:** Methodology, Writing – review & editing. **Jasper van Vliet:** Methodology, Conceptualization, Supervision, Writing – review & editing.

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Declaration of competing interest

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

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Data availability

The code used and the data produced in this study are publicly available from [72].

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