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The impact of spatial resolution on optimal renewable energy portfolios

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Abstract:

Efforts in the energy planning department are required to achieve the target levels of renewable energy penetration and electricity demand in the European Union. Mean-variance analysis is commonly used to identify the optimal deployment of variable renewable energy sources. By using it, we can determine the most effective ways to increase renewable energy penetration and minimise supply risks through varying spatial and technological deployments. In this study, we investigate the effectiveness of optimising capacities at the scale of climate data grid points, rather than administrative regions, which is a common approach due to data availability and computation costs. We find that a finer description of climate resources and variable renewable energy capacity factors results in a better exploitation of complementarities and offers increased degrees of freedom in optimisation. Our analysis reveals that better describing local conditions results in two advantages over lower resolution approaches: higher average capacity factors and generation combinations with lower covariances. Additionally, we find that higher resolution approaches significantly reduce variability in daily and annual climate frequencies in renewable generation under the optimal scenario. These results highlight the importance of accounting for detailed climate information when identifying optimal renewable deployment scenarios and can provide valuable support for stakeholders and policy makers in making sustainable commitments.

Keywords:

Climate energy assessment model; High-resolution energy modeling; Mean-variance analysis; Renewable energy system planning; Spatial resolution.

1. Introduction

The shift towards low-carbon energy systems is a current and future challenge, with the EU setting goals for decarbonization by 2050 [1]. In turn, each country must establish specific measures to achieve these goals. In Spain, there are multidisciplinary plans in place to mitigate climate change [2] and promote renewable energy [3], which emphasize the need for research and the installation of new renewable energy sources, while also recognizing the challenges associated with integrating them into the electricity system.

Solar photovoltaic (PV) and wind energy are the main variable renewable energy (VRE) sources driving the transition towards a highly renewable future, aiming to cover half of the Spanish energy demand due to their improving technology and decreasing costs [4,5]. Spain has seen a significant increase in the installed capacity (IC) of these sources in recent years, with a 156% increase in PV and a 17% increase in wind IC from the end of 2018 to the end of 2020, compared to only a 1% increase in the previous five years for both technologies [6–8]. By the year 2020, the two sources combined reached a mean penetration level of 30%, and installations are planned to grow even further.

While solar radiation and wind drive the energy generation by PV cells and wind turbines, several factors other than the generation potential are involved in planning these installations, including capital and operation costs. Classical approximations follow atlas-derived average capacity factors to estimate the levelized costs of energy for a given technology and location. However, these factors fail to account for the risk posed by the intermittent nature of the resource and the complementarity between different components of the system. This consideration should not be ignored, as taking advantage of the complementarity of the system is crucial in order to minimize electricity supply risks and meet the demand [9, 10]

To ensure renewable energy systems meet certain requirements, optimization methods are commonly used, but the many factors that can vary from one optimization to another emphasize the importance of configuration in planning renewable energy deployment [11] These factors can include constraints, time span, optimization method, and region. In this article, we apply a common approach to optimize the deployment of VRE sources by simultaneously maximizing the mean and minimizing the variance through modifications to the spatial distribution of IC for each VRE source. This straightforward method helps us identify the scenarios with the lowest variance, which serves as a proxy for supply risk, for a given level of penetration and provides optimal scenarios for multiple penetration levels.

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The way generation and demand data are processed and represented is key when applying mean-variance analysis or similar portfolio-based methods. Some studies (e.g. [12, 13]) use regionally aggregated electricity and climatic data in conjunction with portfolio theory to optimize the deployment of VRE across countries or large regions, by using various metrics. However, these results only provide information about optimal deployment for very large areas and do not offer guidance on specific installation locations within those areas. Another approach [14] consists on fixing the total regional IC through an optimization, and then identifying possible deployment locations within each region. This specific allocation of VRE sources uses criteria such as climatic potential and socioeconomic constraints. However, this type of methods could follow initial large-scale distributions that are made under possibly non-representative average conditions.

The process of aggregating different renewable energy generation sites and technologies can lead to a smoothing effect on the generation curve. However, there are alternative approaches to optimization that do not rely on this aggregation, such as using grid-based models or considering existing generation farms as installation points [15, 16]. Despite the more precise description of the system of these methods, they are quite uncommon in the literature [17]. Additionally, obtaining high-resolution data on electricity generation and demand can be challenging, particularly at very high resolutions where the network topology becomes relevant. Nevertheless, the resolution used for optimization is crucial, especially when dealing with highly heterogeneous regions [18, 19].

There is limited research on how different spatial aggregation approaches impact the optimization of renewable energy deployment. Previous studies have looked at a specific form of aggregation, but have not specifically investigated the effects of changes in resolution on the optimal solutions. More extensive research [17] has been done on optimization models, methodologies, and constraints, but there are still no clear answers to the challenges that arise with different levels of resolution.

This article builds upon previous research [20] that investigated the impact of spatial granularity or resolution on renewable energy deployment optimization. However, instead of using administrative regions, this study explores the effects of arbitrary divisions of space on the optimization results, representative of changing resolution. Through a thorough analysis of experiments at varying levels of resolution, we observe the mechanisms that occur as resolution increases and interpret them in relation to the simplifications and underlying drivers of the renewable energy system.

This article is structured as follows: section 2. gives an overview of the methods and data used, section 3. shows and discusses the main results, and finally section 4. summarizes the main conclusions derived from this study.

2. Methods and data

When it comes to implementing renewable energy sources while guaranteeing a stable supply to the network, the challenge can be reduced to a bi-objective optimization problem. This problem involves maximizing the penetration of renewable sources while minimizing the risks of supply failure. To solve this problem, a mean-variance optimization scheme can be used, where the risk is considered as the square root of variance. The resulting set of optimal solutions defines a Pareto front, which represents the minimum variance/risk squared for a fixed mean. In order to optimize renewable energy deployment, the decision variable is the vector of installed capacities of PV and wind at each location, and each location is associated with a specific capacity factor for renewable energy generation. The capacity factor quantifies the percentage of the potential maximum technical production that is actually generated over a period of time. The national demand is also considered, as the primary objective is to determine the optimal generation curve that best matches the demand and its fluctuations, rather than targeting an average specific level of generation.

To optimize the deployment of renewable energy sources, the ratio of national hourly VRE generation to national hourly demand is defined as hourly. However, the model does not constrain the adequacy between generation and demand. This is because the purpose of the mean-variance analysis is to prevent the need to model non-VRE producers that would also contribute to meeting the demand. The mean penetration is then defined as the time average of the hourly penetration series, and risk is defined as its standard deviation. The only constraint set to the capacities is to be non-negative.

We use the e4clim model [21] as our tool, with the consideration of predictable and unpredictable risk [22]. We use ERA5 [23] as the climatic data source, also functioning as out highest resolution grid, and include a nation-wide calibration of generation and demand with electricity data from Red Eléctrica de España (REE). ERA5 has an effective spatial resolution of around 25 km at the latitudes of mainland Spain, with an hourly time step (see Fig. 1a for a reference on the grid and the administrative regions considered). We perform this experiment over a 7-year period with overlapping electricity and climate data, ranging from the years 2014 to 2020. We take the electricity mix at the end of 2020 as a reference, establishing a reference mean penetration of 30%.

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We conducted a series of experiments to investigate how the spatial resolution affects the identification of optimal scenarios for renewable energy deployment. Instead of using traditional administrative regions, we created evenly divided artificial regions across the domain, ranging from the full climatic grid resolution to just four total regions. It should be noted that by considering the regions approach, we assume each of them to be homogeneous and capacity to be evenly distributed. We gradually decrease the resolution of the model by aggregating grid points into larger regions (averaging capacity factors and summing installed capacities) and analyze the impact on optimization results. We then compute a Pareto front for each level of resolution. As the resolution of the model increases, so does the ratio of penetration-risk in the system, resulting in steeper Pareto front slopes (Fig. 1b for the fronts using the whole grid and the administrative regions).

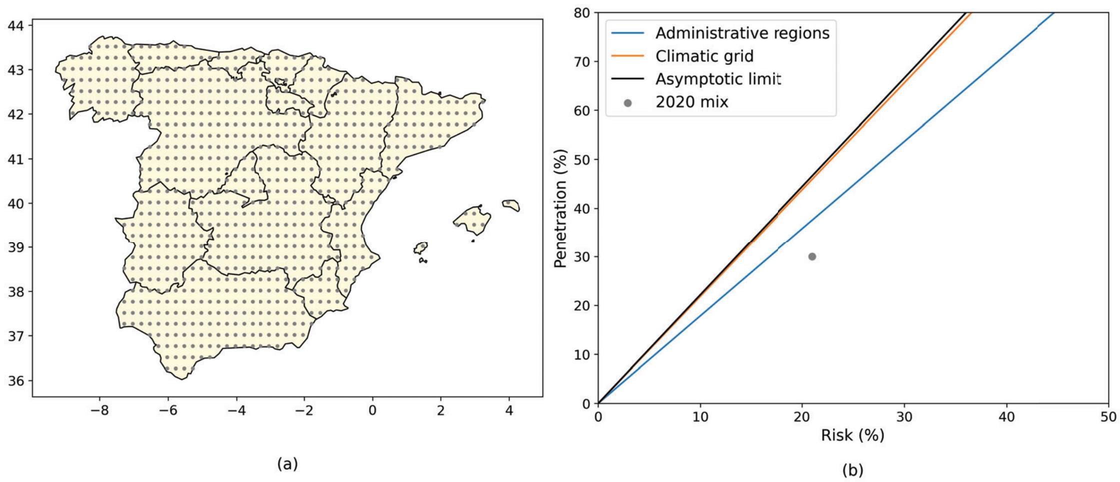

Figure 1: Reference for the administrative regions and full climatic grid approaches in the map (a) and penetration-risk diagram (b). The map (a) shows the full climatic grid over the administrative regions over which they are commonly aggregated. The penetration-risk diagram (b) presents the Pareto fronts for the approaches with administrative regions (blue) and the climatic grid (orange), and for the asymptotic Pareto front (black). The grey dot indicates the location of the 2020 mix.

The Pareto front for each of these experiments is linear in the mean penetration-risk space (fig. 1b). For an arbitrary fixed level of penetration, a minimization of the risk returns the associated capacity distributions for PV and wind. Changing the level of penetration simply introduces a scaling factor to these distributions, which remain the same in relative terms. Therefore, the slope of the Pareto front is constant for each specific resolution, and defines what we call the penetration-risk ratio (PRR).

3. Results and discussion

On a first analysis, we observe that as the resolution of the model increases, there is a corresponding increase in the PRR, with the highest ratio marked by the scenario that uses the full climatic grid. Since the system is powered by climate resources, the extent to which this ratio can increase is limited by the degree to which these resources match the demand. This bounded, increasing behavior indicates the existence of an asymptotic Pareto front, which represents an intrinsic property of the climate driving the system. In this case, ”intrinsic” implies that it is not influenced by the resolution used in the optimization, but it may be affected by the resolution of the climate model used, or the nature of the climate and electricity data that was introduced into the model.

The evolution of the PRR (Fig. 2a) shows a very steep increase at low resolutions, implying that small increments in resolution bring large improvements to the optimization, as the precision in the description of climatic features drastically increases. Once a certain level of resolution is reached, virtually no information is added with increasing resolution because the large climatic modes are already mostly represented, and therefore the PRR practically stabilizes. This implies that the majority of information added at such high resolutions is either redundant, insignificant in relation to the big signals already described, or lacks further resolution from the climatic data. In order to include an analytical dimension that allows us to diagnose the asymptotic behavior of the PRR, we propose a parameterized curve to fit:

$$\mathrm{PRR}(N) = a + \frac{b}{N - c} \tag{1}$$

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where N is the number of spatial divisions over the domain, and representative of the resolution, given that the domain remains unchanged. *a*, *b*, and *c* are parameters to be fitted by the known values of PRR and N at varying resolutions. By definition, the asymptotic Pareto front has the largest PRR possible (as $N \to \infty$), which takes the value of a = 2.22, and would return lower risk for any level of penetration (or higher penetration for any level of risk) than any other possible configuration with a lower resolution (see Fig. 1a). This value describes the best optimal configuration that could exist under the climate conditions as described by ERA5, but changes in the climatic resolution would not necessarily identify the exact same value.

However, we are not interested only in the asymptotic behavior of the PRR, but in the specific impacts on the optimization of a changing resolution. A first approach is to analyze the total installed capacity for each technology at the 30% penetration level and how they change with resolution (Fig. 2b). At low resolutions, high amounts of capacity are needed to reach a fixed level of penetration, even though they produce higher levels of risk. In a directly opposite behavior to the PRR, the capacity necessary to reach a fixed level of penetration decreases with increasing resolution, reaching a similarly asymptote-like behavior on the lowest necessary capacity to install. This behavior stems from the underlying assumption of homogeneity and even installation that is made in the consideration of regions. Since no additional information is given on the specific locations of installations, it is likely that they fall on suboptimal regions within the area, since the optimization used regional divisions. Through this effect, it is also illustrated that considering low resolution aggregated regions can in turn lead to an overestimation of the necessary capacity by nearly 100%, as the decisions on capacity installation are not accounting for the actual climatic potential.

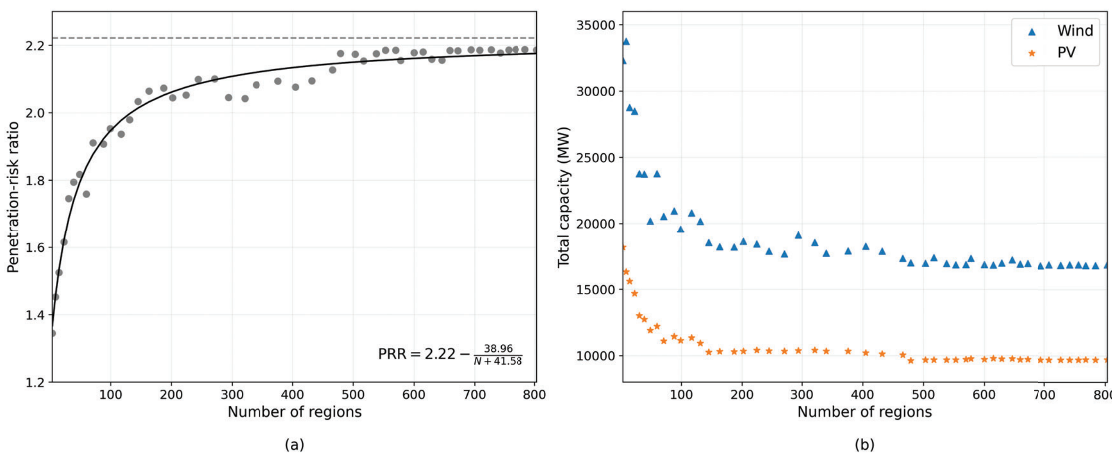

Figure 2: Change with the number of regions of the penetration-risk ratio (a) and total installed capacity per technology at the 30% mean penetration level (b). In (a), the penetration-risk ratio for each number of regions is indicated by a grey dot, the fitting of the points is shown by the solid black line, with the dashed grey line indicating the asymptotic value. The equation for the black line is annotated in the graph, with N the number of regions. For the evolution of capacity (b), the blue triangles indicate the wind capacity, and the orange stars represent the PV installed capacity.

The overestimation of the total installed capacity is an issue that appears in the general vision of the results and that can stem from different causes linked to resolution. In addition to the impacts on total required installed capacity, resolution may also play a role on the spatial distribution of optimal scenarios, which would reveal a significant degrading effect of the regional averaging of the climatic source on the optimization results. An effective method to analyze the spatial dispersion of these distributions is to count the regions with installed capacity exceeding a certain threshold.

Upon analyzing the number of regions with installed capacity exceeding 100 MW at the 30% penetration level, we identify two differentiated behaviors for PV and wind. PV installations (Fig. 3a) are concentrated in a single region across most resolutions, showing no apparent dependence on resolution tendency. This behavior responds to the cyclic nature of PV, which presents little variability across the domain, and is therefore not strongly affected by the averaging process. Indeed, the high covariant component observed in all PV production series within the domain indicates a limited potential for favorable generation complementarities.

The results for wind capacity (Fig. 3b) show a different pattern compared to PV. With increasing resolution, there is a clear tendency for the distribution of installed capacity to spread across a greater number of regions. This suggests that a higher resolution allows for the emergence of more favorable low-covariance combinations

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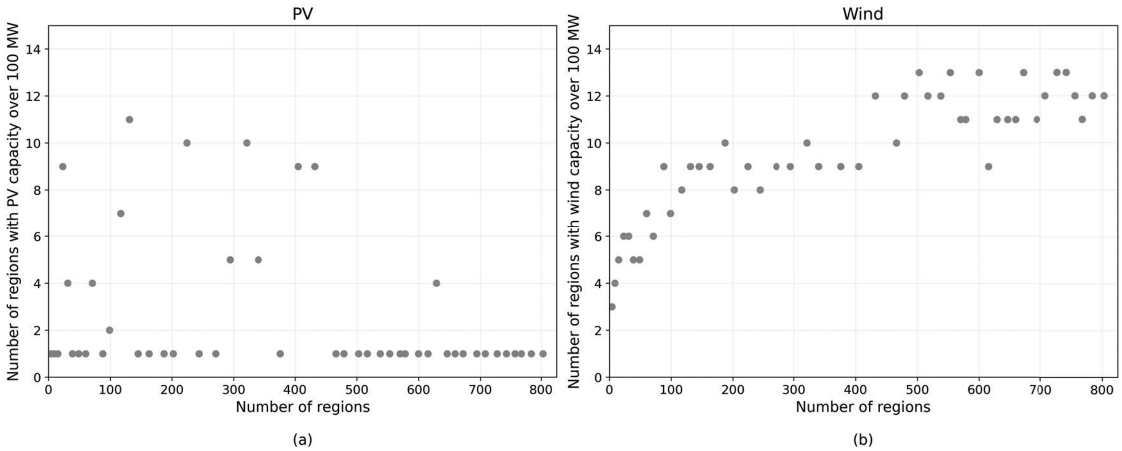

Figure 3: Number of regions exceeding 100MW of installed capacity at a penetration level of 30% at each level of resolution for PV (a) and wind (b).

of wind capacity across different locations. In fact, whereas PV is mostly covariant within the domain, wind resource presents higher variability, and an increased chance for low covariances or even anticovariances to occur is higher. Therefore, using a high enough resolution to capture the potential of favorable low-covariance combinations is key to achieving the maximum actual potential for renewable generation of any given domain.

Thus far, two conclusions that complement the asymptotic PRR results have been drawn. Firstly, the capacity required to achieve a specific level of penetration decreases with resolution, along with the associated risk, due to the better representation of the climatic resource. Secondly, for PV, the capacity tends to be concentrated in a single region, regardless of the modeling resolution, whereas for wind, it spreads across more regions as the resolution increases. These two effects derive from the cyclic quality of PV (following similar patterns all over the domain), and the non-cyclic variable nature of wind.

Therefore, in order to explore the impact of resolution on optimal renewable energy deployment scenarios, the spatial distribution of three resolution levels - low, middle, high - for the 30% penetration target is examined in detail (Fig. 4 a-b, c-d, and e-f, respectively).

The distribution of installed capacity for PV is concentrated in the same region across all three resolution levels, as previously discussed. This suggests that the points that determined the selection of regions in the middle and low resolution scenarios were primarily those located in the region identified by the high resolution scenario. Due to the limited variability of PV, the averaging process does not degrade the results. Additionally, higher resolutions require less capacity in a given region because the optimization more accurately identifies the area with the highest capacity factors and lowest variability, and thus exploits the available climate resources more effectively.

The behavior of wind capacity exhibits two distinct patterns. In the western half of the domain, wind installations behave as PV series in the sense that the entire region follows a similar pattern driven by a substantial influence of sustained strong Atlantic winds. This results in the high resolution wind installations contained within the regions of the middle and low resolution optimal scenarios. On the other side, the eastern half of the domain presents different response. Despite some strong northern winds in the islands and some mountain-influenced winds in the northeast regions, the eastern side of the domain presents very variable patterns, which may not arise at the low and middle resolutions. This is coherent with the more variable Mediterranean climate.

Despite not presenting any installed capacity at the low resolution, the southeastern quadrants of the wind capacity distributions have a region contained in it entering the mix at the middle resolution, and then again presenting zero installed capacity at the high resolution. The capacity allocated at low resolution in the northeast quadrant of the domain, is reallocated differently in the middle and high resolution resulting scenarios. This effect arises from the unique characteristics of each high resolution region being smoothed out when resolution is lowered. The high resolution enables greater detail in the spatial characterization of the climatic resource, allowing previously obscured areas to become visible in the optimal mix. Conversely, areas that were included in the optimal mix at the middle resolution due to the mean, were no longer competitive at the high resolution. The cause behind this is the reduction in region size associated to the increase in resolution. This effect allows high potential areas to stand out without the smoothing effect of the mean, and contrarily considers regions that may stand out only in terms of the mean but that may not contain any smaller areas

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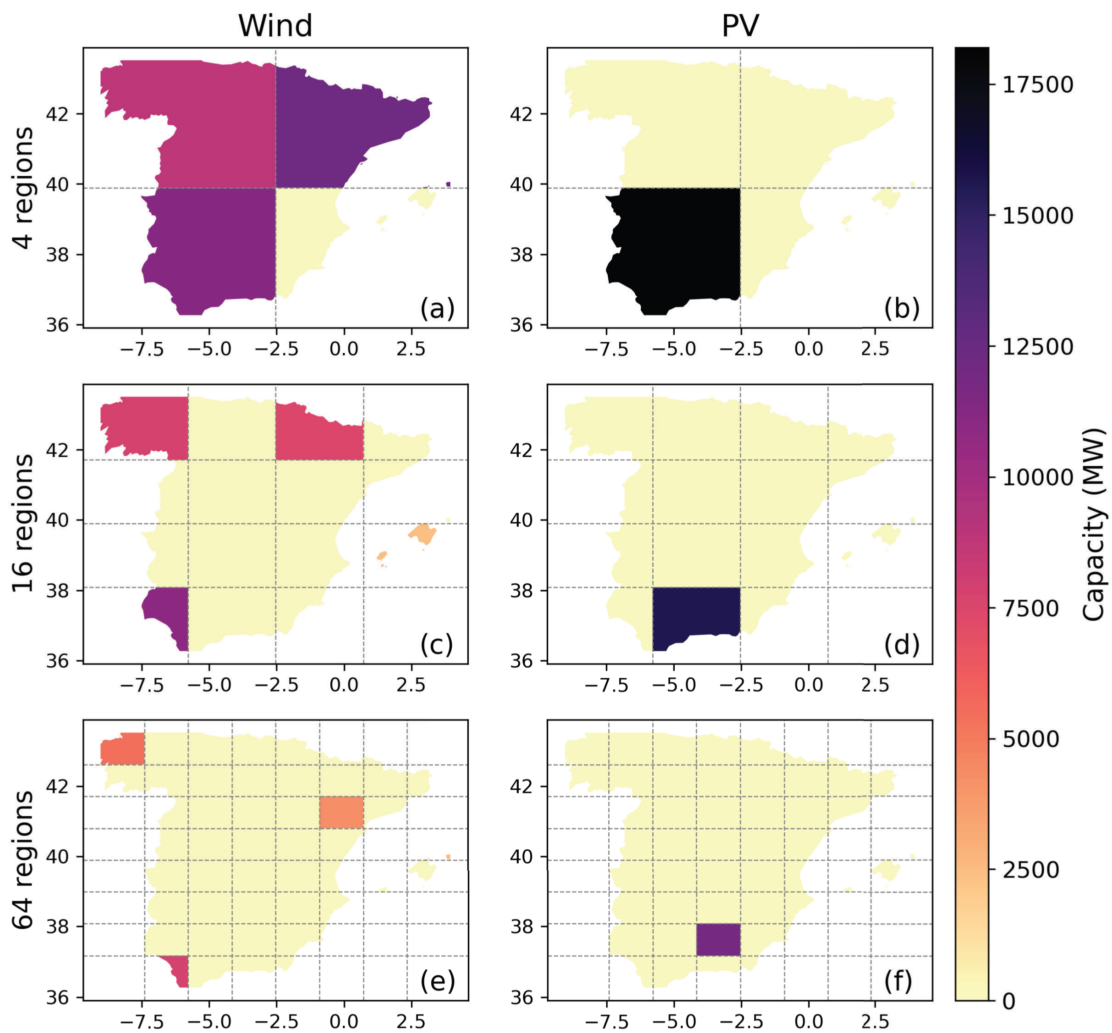

Figure 4: Optimal distribution of installed capacity for wind (a,c,e) and PV (b,d,f) for the configurations with 4 (a, b), 16 (c, d), and 64 (e, f) regions at the 30% penetration level.

of particular potential. This proves key, especially considering that any renewable installation will exploit the corresponding local climatic resource, and not some averaged value.

4. Summary and conclusions

In this article, we determined and analyzed the impacts of resolution on the results of optimization models for VRE deployment. By simple asymptotic reasoning, the absolute limit in penetration-risk ratio for a certain spatio-temporal distribution of climate resource and electricity demand is derived and represented by the asymptotic Pareto front of the system.

The usable resolutions in renewable energy deployment optimization models are primarily bounded by climate data resolution. The intrinsic limit of the attainable penetration-risk ratio can be represented by the asymptotic Pareto front, which provides an estimate of the upper limit in terms of renewable penetration-risk payoff given the available resource. The illustrative example of Spain renders a penetration-risk maximum payoff of 2.22, and therefore the Spanish VRE system should assume a minimum risk threshold of 45% in order to achieve 100% penetration. This front is independent of the resolution used for the optimization, but not necessarily independent of the climate data and its resolution. We find that the frontier reached when using the full climate grid optimization closely approximates the asymptotic behavior of increasing resolution, with minimal differences in penetration and/or risk under 1% at any given level.

Both PV and wind technologies exhibit similar patterns in terms of the total installed capacity, and with increases in penetration, the necessary capacity decreases while also lowering the risk, as a result of more accurate descriptions of the real climatic reality. However, they show different behaviors when the actual distributions of capacity are considered. PV tends to have all its capacity concentrated in one region. By its nature, PV follows a similar pattern over the whole domain (i.e., the predictable daily and seasonal cycles), which implies that the potential benefits of combining different installation location are small. Contrarily, wind presents a more varying nature over the territory, which in turn favors instances where combining wind resources is beneficial to the overall system. As a result of this changing quality, wind capacity distribution varies with the changing resolution due to some high-potential areas being averaged out across regions, as well as some regions having better averaged values than their individual components. However, in areas with strong sustained wind patterns, wind capacity follows a similar behavior to PV.

The use of higher resolution data can prevent overestimations of necessary capacity. The usage of the highest possible resolution helps identify the synergies between different locations for installation. In turn, these synergies allow for smaller amounts of installed capacity to reach high penetration levels. Lower resolution approaches limit the possible combinations and the precision of their components, which presents a reduced representation of reality that is detrimental both in terms of return and in terms of necessary capacity.

Acknowledgments

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