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Wind-solar technological, spatial and temporal complementarities in Europe: A portfolio approach

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ABSTRACT

Climate change and geopolitical risks call for the rapid transformation of electricity systems worldwide, with Europe at the forefront. Wind and solar are the lowest cost, lowest risk, and cleanest energy sources, but their variability poses integration challenges. Combining both technologies and integrating regions with dissimilar generation patterns optimizes the trade-off between maximizing energy output and minimizing its variability, which respectively give the lowest levelized cost and lowest integration cost. We apply the Markowitz mean-variance framework to a rich multi-decade dataset of wind and solar productivity to quantify the potential benefits of spatially integration of renewables across European countries at hourly, daily and monthly timescales. We find that optimal cross-country coordination of wind and solar capacities across Europe's integrated electricity system increases capacity factor by 22% while reducing hourly variability by 26%. We show limited benefits to solar integration due to consistent output profiles across Europe. Greater wind integration yields larger benefits due to the diversity of regional weather patterns. This framework shows the importance of considering renewable projects not in isolation, but as interconnected parts of a pan-continental system. Our results can guide policymakers towards strategic energy plans that reduce system-wide costs of renewable electricity, accelerating the clean energy transition.

1. Introduction

The urgency to mitigate climate change [1], combined with the European energy crisis [2] calls for a rapid transition from fossil fuels to renewable energy sources [3]. The main challenge to achieve this rapid transition is the integration costs caused by the variability of wind and solar power [4,5]. There are three main mechanisms to integrate higher shares of variable renewables: energy storage [6–8], demand management [9] and spatial integration [10,11]. We focus on the potential benefits of spatial integration and deployment coordination of variable renewable energy (VRE) technologies across countries to optimize the trade-off between achieving the maximum possible capacity factor (CF) energy output with the lowest possible variability.

We exploit a rich dataset of simulated wind (onshore and offshore) and solar photovoltaics (PV) hourly CF for 30 years for European countries to explore the potential benefits of optimally deploying variable renewable energy capacities across countries. We use the Markowitz mean-variance model to calculate optimal portfolios of shares of installed capacities per country and technology that can achieve the highest possible capacity factor (CF: energy generated per unit of installed capacity) per unit of variability (here measured as the standard deviation (SD) of the CF). This allows us to identify and quantify benefits in three dimensions: spatial (across countries), temporal (at different timescales) and technological (solar, onshore and offshore wind). We evaluate the benefits of integrating electricity systems, from autarky to a pan-European system, at three different timescales: hourly, daily and monthly. Likewise, we assess the effects of optimizing the capacity shares of each renewable energy technology both across countries of integrated electricity systems and within countries in autarky. We exclude dispatchable (such as biomass) and baseload (such as geothermal) technologies as their CF is controllable and not spatially-dependent on the weather. Whereas there may be other variable renewable energy technologies, such as wave and tidal, we

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Abbreviations

**2-letter country codes according to the ISO 3166 standard*

CF	capacity factor
CRF	capital recovery factor
CV	coefficient of variation
CVaR	conditional value at risk
CWE	Central West Europe (Benelux, France and Germany)
IC	installation cost
IPCC	International Panel for Climate Change
LCOE	levelized cost of electricity
NWE	North-Western Europe (CWE, Great Britain, the Nordics and the Baltics)
MPT	Modern Portfolio Theory
O&M	operation and maintenance
SD	standard deviation
PV	photovoltaic
VRE	variable renewable energy

exclude them because they have not achieved market maturity and they are expected to represent a marginal share of electricity demand according to the International Energy Agency [12].

We find that solar and wind technologies are complementary, and optimizing their relative shares helps optimize the CF-SD trade-off. The integration of solar power across European countries does not provide significant benefits because generation patterns within the continent are homogeneous and the Southern countries have both higher and more consistent solar resource. However, the benefits of wind integration across countries are large thanks to its more heterogeneous generation patterns across countries, and it provides additional benefits when optimally combined with solar resources.

Finally, we create a European Union (excluding Malta and Cyprus and including Great Britain) case study to quantify the potential benefits of optimizing the shares of variable renewable installed capacities across countries and show that the EU reference scenarios for decarbonization until 2050 do not seem to take these potential benefits into account. Because higher CF translates into lower unit costs and lower variability translates into lower integration cost (ceteris paribus), our framework may help design a lower-cost Europe-wide electricity system that can speed up the adoption and integration of variable renewables. Additionally, because we provide the optimal portfolios as well as the efficient frontiers, we shed light on potential near-optimal solutions that may be more feasible in real life when integrating a variety of other allocation criteria, such as transmission cost, landscape conservation, interregional equity, etc [13].

The remainder of the paper is structured as follows. Section 2 reviews the background on renewable energy complementarities and modern portfolio theory. Section 3 presents the data sources, their main characteristics and descriptive statistics. Section 4 explains how we apply modern portfolio theory to the optimization of renewable energy capacities across technologies, countries and timescales. Section 5 presents the results, focusing first on the benefits of spatially integrating individual variable renewable energy resources, to then combine the different technologies. Finally we build a case-study for the European Union comparing the actual current situation and the plans of the EU reference scenarios with the current and future optimal solutions. We provide potential benefits both in terms of the CF-variability trade-off and unit generation costs (LCOE: levelized cost of electricity). Section 6 concludes and discusses implications for policy and research. Fig. 1 summarizes the structure of the analysis.

2. Background

2.1. Renewable energy complementarities

Wind and solar complementarities have been studied from several perspectives and at different temporal and spatial scales. Some studies focus on the potential of spatial integration of different regions for a single technology: for wind at continental [14] [15,16] and intercontinental levels [17] and for solar at interhemispheric level [18]. Other papers study the complementarity between wind and solar in Germany [19], China [20], Rusia [33], Europe [21], North America [22] and even at global level [23]. All these studies find that integrating locations and technologies provides complementarities in terms of lower variability.

Weschenfelder et al. [24] provides a review of recent literature identifying correlations and standard deviations as the main methods to quantify complementarities. Whereas correlations are well studied in the literature, few papers consider the trade-offs of achieving a flatter generation profile by combining technologies and locations, namely, the reduction of potential capacity factors. For this reason, we propose a comprehensive framework to assess the trade-off between achieving the maximum possible capacity factor and the minimum possible variability by combining technologies and regions at different spatial and time scales using modern portfolio theory in Europe.

2.2. Modern portfolio theory applied to energy planning

Modern Portfolio Theory (MPT) is a quadratic optimization methodology, initially suggested by Markowitz [25] and widely developed in the field of finance, to solve the trade-off between an investment's

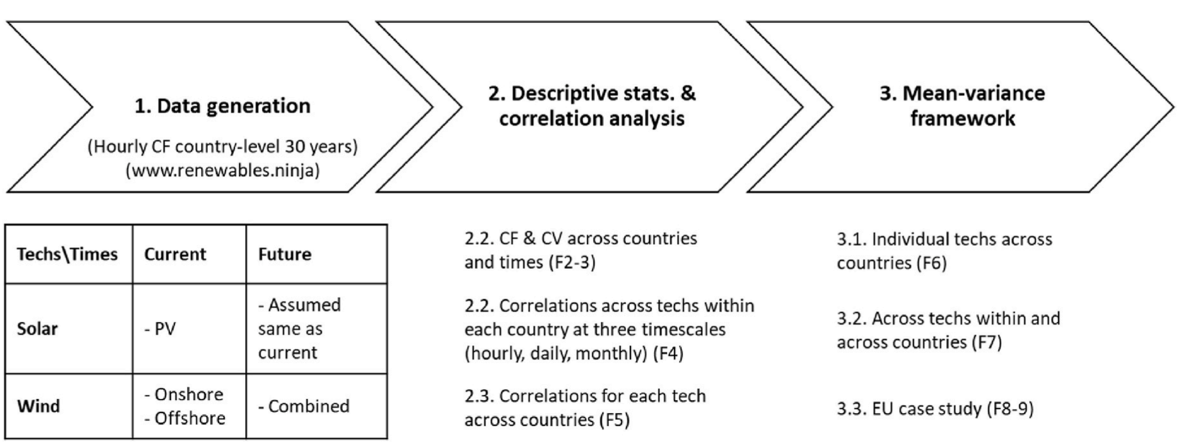

Fig. 1. Structure of the analysis for assessing the trade-offs between mean capacity factor (CF) and its standard deviation (SD). Figures in the paper relating to each stage of the analysis are denoted by "F" in brackets.

portfolio risk and return. The optimization process may consist of either maximizing the expected return for each level or risk, or equivalently minimizing risk for each level of expected return, subject to a number of technical constraints. Whereas in financial applications the portfolio is a combination of different financial assets, we here optimize the allocation of wind and solar capacities across countries. We use hourly CF instead of daily returns and their SD is our measure of risk.

For the last twenty years, MPT has also been used as a tool to design efficient portfolios of different electricity generation technologies. Since the first studies using this approach [26], electricity system capacity planning has been addressed as a decision-making problem about future real asset investment. The first adaptations of MPT to energy planning defined the return of the energy portfolio as the inverse of the generation cost [26]. Since then, other alternatives have been proposed, such as the cost-risk models based on the calculation of LCOEs for each electricity generation technology [27–29], discounted cash flows approaches through net present value and internal rates of return criteria [30], or considering power generation prices and costs of specific markets [31].

Because VRE technologies have no fuel costs, including them in a portfolio decreases the risk compared to fossil fuels in approaches that use any variant of cost as the return indicator [28,29]. Among renewable sources, wind energy stands out because its deployment results in a very positive impact in terms of return and expected risk reduction [32,33]. By using this methodological approach, some authors have already highlighted potential benefits of combining wind and solar to reduce the probability of supply disruption and therefore achieve a lower level of risk [33–36]. Including some methodological innovations to solve in the original problem, Garcia et al. [37] focus on the application of a conditional value at risk (CVaR) measure from the point of view of the market performance of a utility portfolio. Finally, Unni et al. [35] and Castro et al. [38] implement the CVaR to minimize the risk of supply disruption.

Specifically addressing the problem of setting the geographical location of wind farms using MPT, Roques et al. [39] estimate the optimal allocation of wind capacity in 5 European countries. Likewise, Nishiyama et al. [40] study the optimal siting of wind farms within three prefectures of northern Japan at high resolution. Shahriari and Blumsack [41] estimate the capacity values of VRE when optimally deploying capacity across the USA. Most similar to our study, Hu et al. [42] analyse the complementarities of wind and solar installations across China. Finally, it is worth mentioning a number of outstanding works focusing on the best location and distribution for wind farms in order to optimize production and reduce the intermittency of production [43–45]. Scala et al. [34] conclude that the study of time series may also help in decision-making for the location of energy storage facilities, necessary to compensate for the variability of renewable energies.

We build upon this previous literature (summarized in Table 1) and present a comprehensive study of wind-solar complementarity in Europe combining three dimensions: (i) three technologies (wind onshore and offshore and solar photovoltaics), (ii) three timescales (hourly, daily and monthly) and (iii) different levels of spatial integration from countries in autarky to a pan-European system, finishing with a more realistic EU (plus Great Britain minus Malta and Cyprus) case-study. Our contribution is therefore twofold: we provide a detailed analysis of wind-solar complementarity in Europe across these three dimensions (spatial, temporal and technological); and we show potential pathways of sequential integration from autarky to a pan-European electricity system through increasingly larger spatial configurations.

3. Data

3.1. Renewables.ninja data on wind and solar power output

We use the Renewables.ninja models to simulate the CF of wind and solar PV farms across Europe. These provide hourly time-series of the power produced from individual wind and solar installations by

Table 1
Modern portfolio theory for energy planning literature review summary.

Authors	Year	Region	Highlights
Awerbuch and Berger [26]	2003	European Union	Renewable technologies are defined as real assets without risk, as costs can be established a priori. They establish the optimal mix of technologies for the EU by 2010. Return is defined as the inverse of cost and the aim is to maximize the overall return of the energy technology portfolio.
Awerbuch and Yang [28]	2007	European Union	The authors shift to a cost-risk approach to technologies. They consider renewable technologies as risk-free assets and emphasize the importance of risk diversification due to the existence of zero and negative correlation coefficients.
Muñoz et al. [30]	2009	Spain	The model maximizes return, which is based on cash-flows calculations. Using an economic model, the authors calculate the distribution of the Internal Rate of Return (IRR). They also highlight the relevance of negative correlations between the risks of technologies to minimize the portfolio risk.
Roques et al. [39]	2010	Austria, Denmark, France, Germany and Spain	Portfolio theory is implemented in order to identify the composition of the portfolios of five European countries. The aim is to minimize the total variance of wind production for a given output level. If no technical constraints are included in the model, Spain and Denmark are preferred as in these two countries the best wind resource is available or the variability of production is clearly reduced by size. By including constraints, the results confirm the need for greater cross-border interconnection capacity as well as designing and implementing incentives for wind farm siting at the European level to reduce the associated costs of balancing and system reliability.
Allan et al. [27]	2011	Scotland	Optimization approach based on minimizing cost and risk. Stemming from the correlation of fuel costs and renewables costs, the benefits of diversification are highlighted. They also confirm the benefits of including renewables in the portfolio in terms of risk reduction, without increasing costs.
Delarue et al. [32]	2011	Theoretical model	A portfolio theoretical model making an explicit difference among installed capacity (power), electricity generation (energy) and real instantaneous power supply is proposed. They also include the variability of wind power and the ramp limits of traditional power plants. The results confirm that introducing wind power in the portfolio can reduce the risk in the cost of

(continued on next page)

Table 1 (*continued*)

Authors	Year	Region	Highlights
			generation, although at lower levels than those usually reported in the literature. In addition, technologies that cover its intermittency in the system are required.
Gökgöz and Atmaca [31]	2012	Turkey	Focuses on electricity generation assets allocation when implementing bilateral contracts (forward contracts and daily spot market). It is based on portfolio optimization in electricity market using spot market hourly prices separately as risky assets, considering no transmission congestion in the system
deLlano-Paz et al. [29]	2015	European Union	Includes the concept of externality in the cost-risk portfolio model based on minimizing the risk of the cost of the different technologies. Including externalities in the model leads to a greater importance of renewable technologies, as they contribute to risk minimisation.
Joubert and Vermeulen [43]	2016	South África	Optimizes the location and size of wind farms to reduce their variability. The authors also confirm the usefulness of using clustered datasets to minimize variability and increase the energy yield of a set of wind farms by finding their best location and size.
García et al. [37]	2017	PJM Market	Analyzes the optimal allocation of a utility's energy portfolio in daily unregulated electricity markets. They propose two MPT models (mean-variance and Conditional Value at Risk). Combined with a GARCH prediction technique, the day-ahead electricity prices are forecasted. The results confirm that the higher the investor's risk aversion, the lower the participation of the spot market in the portfolio, due to its volatility.
Sosnina and Shalukho [33]	2017	Technical model	Proposes an operational risk indicator to manage operational risk in power systems with RES. It is calculated using Portfolio Theory. Variables considered are type, production and capacity of power plants. Results of 360 combinations confirm the decrease of the value of this indicator if the correlation factor between renewable energy power plants is negative.
Sabolić et al. [44]	2017	Croatia	Seeks to reduce the variability of wind power using portfolio theory. As the wind power data sample do not follow a Gaussian distribution, some different distributions are used. The aim is to minimize the variability of wind power generation using the optimization model. They highlight that location of new plants should take into account previous geographical locations and the importance of using

Table 1 (*continued*)

Authors	Year	Region	Highlights
			optimization models that enable the removal of inefficiencies.
Zhang et al. [36]	2018	China	Focuses on the optimal composition of the Chinese technology portfolio for 2030 under different scenarios. The conclusion is that the advantages of fossil generation technologies get reduced when technical constraints are included in the model. The introduction of policy targets as well as cost and risk reduction and diversification objectives lead to a stronger presence of renewables.
Shahriari and Blumsack [41]	2018	Electric grid in the Eastern United States of America	Incorporates portfolio theory to analyse the diversification benefits by quantifying the influence of spatial and temporal scale aggregation of wind power. They conclude that the greater the geographic diversification, the lower the risk. Adding solar technology to wind portfolios increases the availability factor of the portfolio by over 40%. Finally, they found that the greater the temporal disaggregation, the greater the availability of the renewable resource.
Baeza and Farías [45]	2018	Chile	Proposes a mean-variance model to allocate the installation capacity among wind farms. It aims to minimize the overall variability of wind power for given average power levels. They suggest using the average daily standard deviation of wind power generation as a measure. They work with four wind power scenarios for Chile 2030. For the same nominal capacity, higher production and lower variability is obtained as compared with the base scenario.
Nishiyama et al. [40]	2019	Japan	Proposes an automated site selection model for new wind farm installations. The analyzed area is one square kilometer. Using geographic features such as altitude and wind speed, they identify feasible regions to host wind farms in the aforementioned area. The model includes constraints that seek to maximize the average annual wind speed (production optimization) or minimize the covariance between the production of each cell (production stabilization). Portfolio theory is used to evaluate the efficiency of site portfolios. Clustering of zones maximizes the average wind speed and reduces the variability of output per site.
Hu et al. [42]	2019	China	Focuses on the variability of renewable production, the need for greater backup and reserve capacity. They propose combined portfolios including wind and solar technologies due

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Table 1 (*continued*)

Authors	Year	Region	Highlights
			to their better performance compared to portfolios consisting entirely of one of them. As renewable technologies are deployed over a wide area, the variability associated with their intermittency is reduced. They suggest that when not including restrictions on the participation of renewables, the model leads to better result than when they are included. Therefore, they conclude that the outcomes of works or models including such restrictions tend to bear higher levels of inefficiency.
Scala et al. [34]	2019	Italy	Puts forward a portfolio model based on Gaussian fluctuations with tunable correlations. They seek an efficient trade-off between production and production variability. Including time series analysis in the model may help make decisions on the size and location of energy storage facilities.
Unni et al. [35]	2020	India	Seeks to set the optimal combination of renewable and hydro technologies in the production mix. They carry out the optimization process by including economic and energy production parameters through a fuzzy generated index. They propose a multi-objective approach considering the investor's degree of risk aversion. Including solar, wind and hydro technologies, two different magnitudes are considered: average monthly energy produced and profit to obtain the index. They conclude that mean-CVaR optimization improves mean-variance allocation.
Castro et al. [38]	2022	Brazil	Highlights that many of the portfolios obtained from a mean-variance optimization model have a high probability of underproduction in those locations with low or high standard deviation. They confirm that diversification plays an important role in stabilizing the production of portfolios based on variable renewable sources. In the proposal, they include the correlation between demand and generation profiles and limit break risks thanks to the consideration of CVaR.

combining historical weather data with physical models of wind turbine and solar cell operation. The simulations used here represent power production from the current installed fleet of wind and solar power, and a potential future fleet for wind farms, if they had operated through 30 years of historical weather. Simulations were made at the individual farm scale, and aggregated up to national scale for the 27 countries of the EU plus Norway, Switzerland and Great Britain.

We extracted meteorological variables for air temperature, solar irradiance (at the surface and top of atmosphere), and wind speed (at three heights above ground) from the MERRA-2 reanalysis [46] for the years 1980–2019. These were converted to capacity factors (defined as the ratio of instantaneous power output to installed capacity) using the Global Solar Energy Estimator [47] and Virtual Wind Farm [48] models, which are available open source.[1]

For solar PV, there are no consistent data on the spatial distribution of Europe's utility and rooftop PV systems. We therefore modelled a single crystalline PV installation in each grid cell of MERRA-2, specified at a resolution of 0.5° latitude and 0.625° longitude, and assigned each cell to its respective country. Panels were assumed to have a fixed orientation, with tilt and azimuth drawn from normal distribution according to the known panel angles from a database of PV installations in Europe [21].

For wind, we simulated the output of each wind farm over 1 MW in capacity installed as of 2019, using the 10,189 farms (119 GW of capacity) listed in "The Wind Power" database [49]. The specific location and characteristics of each wind farm (installed capacity, turbine model and hub height) were accounted for in the simulations, and any missing meta-data were inferred using multivariate regression as in Staffell and Pfenninger [50]. For the potential future fleet of wind farms (c. 2030) we also included the pipeline of offshore wind projects under commercial consideration (an additional 478 farms and 101 GW of capacity). Simulations of this future fleet account for three factors which can increase capacity factors: location, hub height and turbine model. First, as this fleet is composed of specific projects which are in the planning pipeline, it explicitly represents the move towards offshore locations with higher wind resources which are typically further from coastlines, with a concentration of planned wind farms in the Dogger Bank area of the North Sea [51]. Secondly, these planned projects have 14% taller hub heights: with a mean of 109 m compared to 81 m for offshore wind farms in the current fleet. As wind speeds increase approximately with the logarithm of height, this confers slightly higher capacity factors which are accounted for in the simulations. Finally, the future wind fleet contains meta-data on the turbine models that developers plan to use, which are on average 70% larger (in terms of MW generator capacity) than the current fleet of offshore farms. This includes next-generation turbines such as the GE Haliade-X and MHI-Vestas V164, which are anticipated to offer higher capacity factors. Turbine models such as these which were at the prototype stage (and thus did not have published power curves) were modelled using power curves simulated using the WTPCM model [52].

A key advantage of our data is that its accuracy and robustness have been verified through validation against historical metered power output data across European countries [47,48]. Capacity factors are bias-corrected to remove systematic over-estimation of wind speed and irradiance in the input meteorological data, and the lack of microscale spatial resolution which prevents MERRA-2 from capturing local terrain effects on airflow. Previous work has shown that Renewables.ninja can simulate the hourly capacity factors for the national renewable fleets with a root-mean squared error (RMSE) of 1.4% for wind and 3.3% for solar across Europe [47,48]. The dataset used here is available to download with an open-access license on www.renewables.ninja.

3.2. Descriptive statistics

The hourly CF is an essential parameter for VRE technologies. The mean CF indicates how much electricity the specific technology can generate in a given location per unit of installed capacity, which determines its unit cost (LCOE) given installation cost. Additionally, the variability of the hourly CF (measured here as its standard deviation, SD) determines the amount of flexible capacity necessary to integrate higher shares of VRE and therefore the integration cost they cause to the

[1] See https://www.renewables.ninja.

electricity system. Fig. 2 summarizes these properties showing the average CF and the coefficient of variation ($CV = SD/\overline{CF}$) for solar, onshore wind and offshore wind for European countries. In most countries, onshore wind has a higher CF than solar, and in the countries where offshore wind is available, this is the highest of the three (Fig. 2a). Norway, France and Sweden present particularly high offshore wind CF above 45%, whereas in all the other countries, offshore wind CF ranges between 30 and 40%. Solar CF is more homogeneous across European countries ranging mostly between 10 and 20%, and being consistently higher at lower latitudes. The CF of onshore wind is more diverse across countries, ranging between 10 and 30%. The variability of solar is determined by its diurnal and seasonal cycles, both of which are homogeneous within the same hemisphere, but stronger at higher latitudes. Countries farther away from the equator tend to have higher coefficients of variation (Fig. 2b), ranging between 1.3 and 1.7. Wind has softer diurnal and seasonal cycles, and more heterogeneity across countries. Variability is therefore usually lower for wind than for solar.

Wind power technologies are developing, both by introducing new turbine designs that provide higher CF, and by expanding to new areas in seas and oceans that were previously beyond reach [53]. For this reason, we combine the current data presented in section 3.1 and Fig. 2 with projections of future wind CF according to these expected developments. Fig. 3 shows the current and expected future CF and coefficient of variation for wind power across countries. Wind CF are expected to remain constant or increase in all countries except Finland and Romania that will experience a slight decline. Likewise, the coefficient of variation remains constant or decreases for all countries except Finland and Poland.

In summary, we work with 4 different datasets of simulated hourly capacity factors for 30 years in European countries: (i) current solar, (ii) current aggregated wind, (iii) current wind disaggregated into onshore and offshore, and (iv) future aggregated wind. The full dataset contains more than 21 million observations. We exploit the richness of these data to derive insights about renewable energy complementarities across three dimensions: spatial, temporal and technological. The data and replication code are publicly available (see Data availability section).

3.3. Technological and geographical complementarity

Different regions have different generation patterns. For this reason,

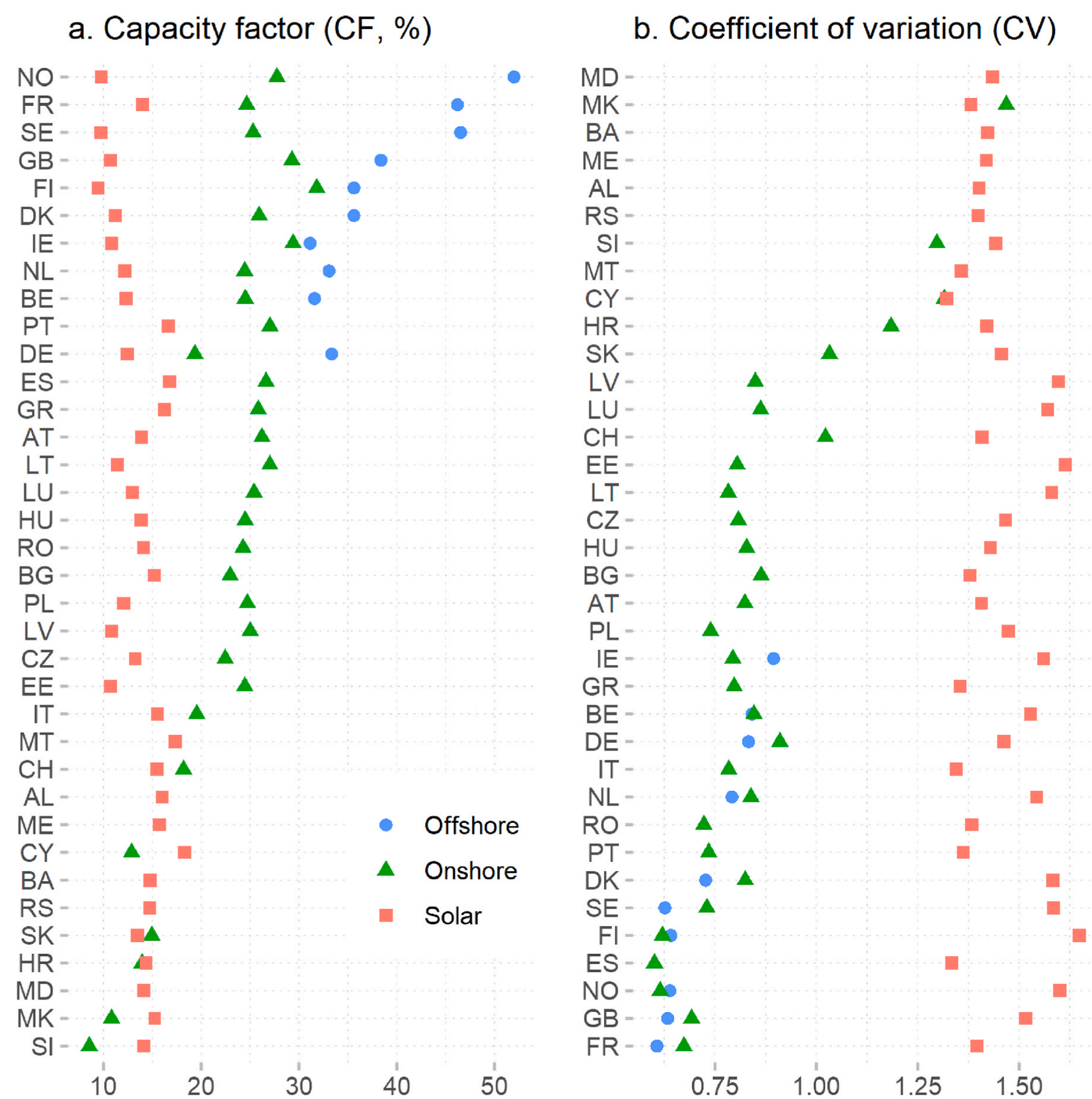

Fig. 2. Capacity factor (a) and coefficient of variation (b) per country and technology sorted in descending order of the average across technologies.

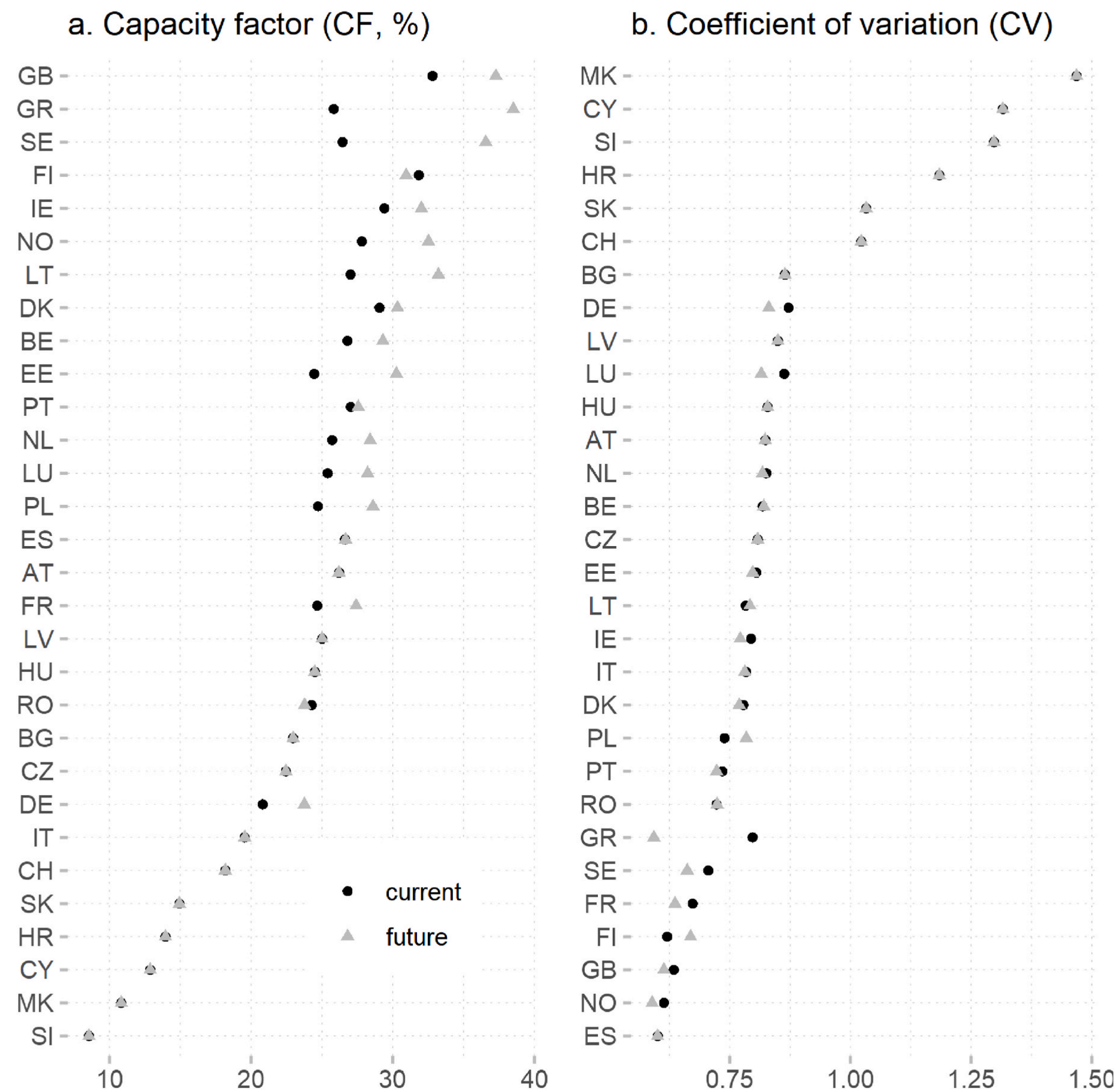

Fig. 3. Capacity factor (a) and coefficient of variation (b) per country for wind power at the current and future timeframe sorted in descending order of the average across timeframes.

integrating areas with opposite generation patterns would smoothen the aggregate generation profile. Our aim is to identify and quantify the complementarities between VRE technologies to achieve a less variable generation pattern at the highest possible capacity factor (and thus lower unit cost, ceteris paribus). These complementarities can be achieved by combining two technologies with opposite generation patterns in the same regions (Fig. 4), or by integrating regions with opposite generation patterns (Fig. 5).

Wind and solar power are complementary as their generation profiles have a negative correlation. Fig. 4 shows wind-solar complementarity depending on the timescale for each European country. The larger the timescale, the higher the complementarity between both technologies (i.e. stronger negative correlation). Solar and wind are very complementary at the seasonal level, due to summer having lowest wind speeds but highest irradiance, and vice versa during winter.

Solar generation is homogeneous across countries (Fig. 5a), so spatial integration of solar resources helps reduce short-term intermittency but does not provide significant synergies at higher timescales. On the contrary, wind generation is more location-specific (Fig. 5b), so combining regions with opposite patterns smooths the aggregate generation profile. Figs. 4 and 5 show that the combination of wind and solar can reduce the overall seasonality of VRE generation and, to a lesser extent, also reduce daily and hourly variability. The integration of solar energy across countries in Europe is not likely to bring significant benefits due to the highly correlated generation patterns across countries, but wind power integration can bring benefits thanks to the higher heterogeneity of wind generation patterns across countries. The rest of this paper formalizes this analysis by adapting modern portfolio theory to quantify these potential benefits.

4. Method

4.1. Mean-variance framework

Our goal is to optimize the trade-off between high renewable generation per unit of installed capacity (CF) and low variability (SD). For this purpose, we combine installed capacities of different VRE (wind onshore and offshore and solar) across countries. In this framework, the equivalent to an asset in the traditional modern portfolio approach is the installed capacity of each technology in each country, and the asset's

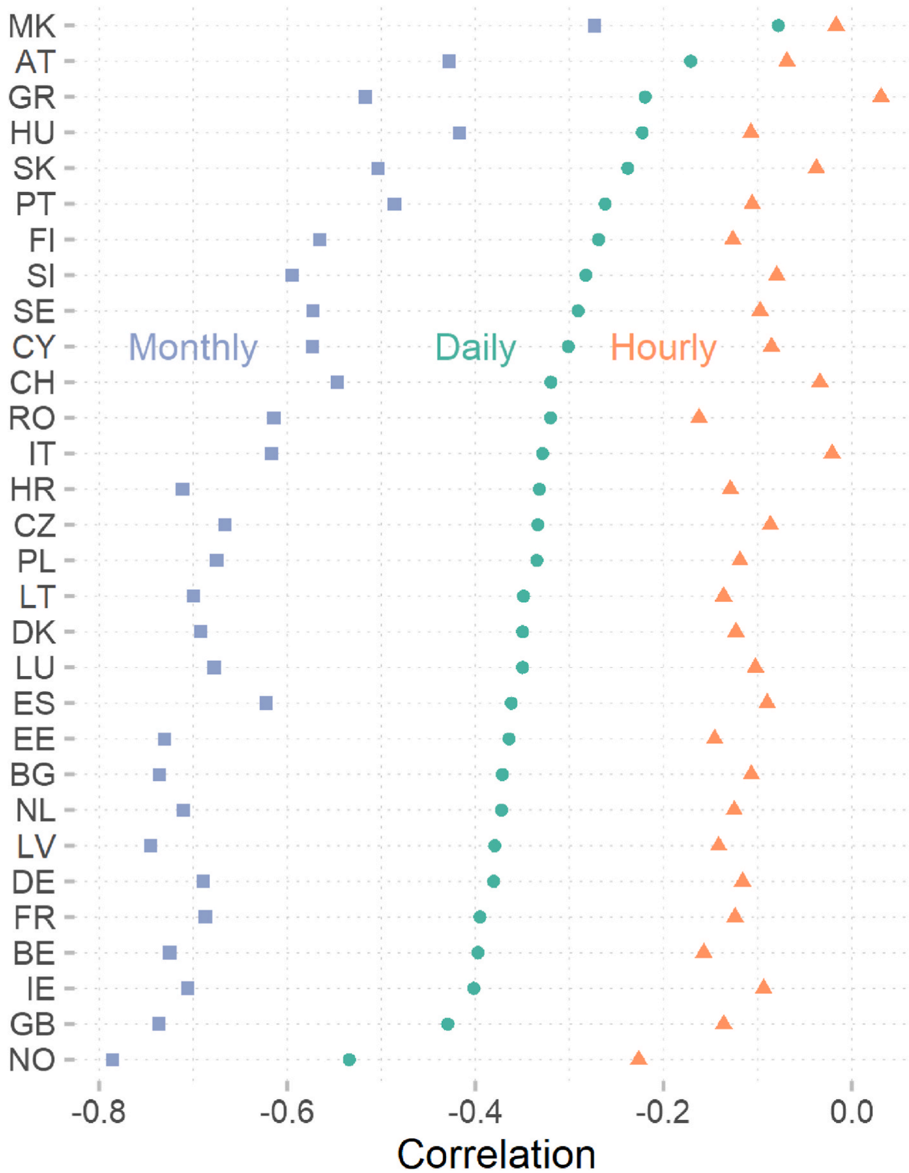

Fig. 4. Correlation between solar and wind capacity factors at hourly, daily and monthly timescales within each country, sorted in descending order.

weight in the portfolio is the share of installed capacity of the specific technology in a country with respect to the total installed capacity in the system. In summary, we want to obtain a portfolio of VRE installed capacities across countries that minimizes SD for each attainable CF. The expected CF of the portfolio ($E(CF_p)$) is simply the weighted average of each technology-country (i) expected capacity factor ($E(CF_i)$) times the share of this technology-country on the total installed capacity (X_i):

$$E(CF_p) = \sum_{i=1}^{N} X_i E(CF_i)$$

Likewise, the portfolio SD (σ_p) is the sum of each asset's SD weighted by its share over the total portfolio and the covariance of each pair of assets weighted by their respective shares:

$$\sigma_p = \sqrt{\sum_{i=1}^{N} X_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} X_i X_j p_{ij} \sigma_i \sigma_j}$$

where X are the ith and jth assets' weights (i.e. the share of installed capacity of a technology in a country) for the N technology-country combinations, σ_i are their respective standard deviations and p_{ij} are the correlations between the ith and jth assets.

We thus want to identify the weights of the assets (X_i) that minimize the portfolio standard deviation σ_p subject to a "full-investment" constraint (i.e. the sums of weights must be 1), a non-negativity constraint (i.e. the shares of installed capacities have to be zero or positive), and for each attainable CF that we set exogenously iteratively to build an efficient frontier of portfolios that have the minimum possible variability for each expected CF.

$$Min(\sigma_i)$$

$$s.t. \sum_{i=1}^{N} X_i = 1;$$

$$X_i \in \mathbb{R} \geq 0;$$

$$E(CF_p) = c$$

where c is a vector of attainable portfolio expected CF.

The result of this optimization is a vector of shares of installed ca-

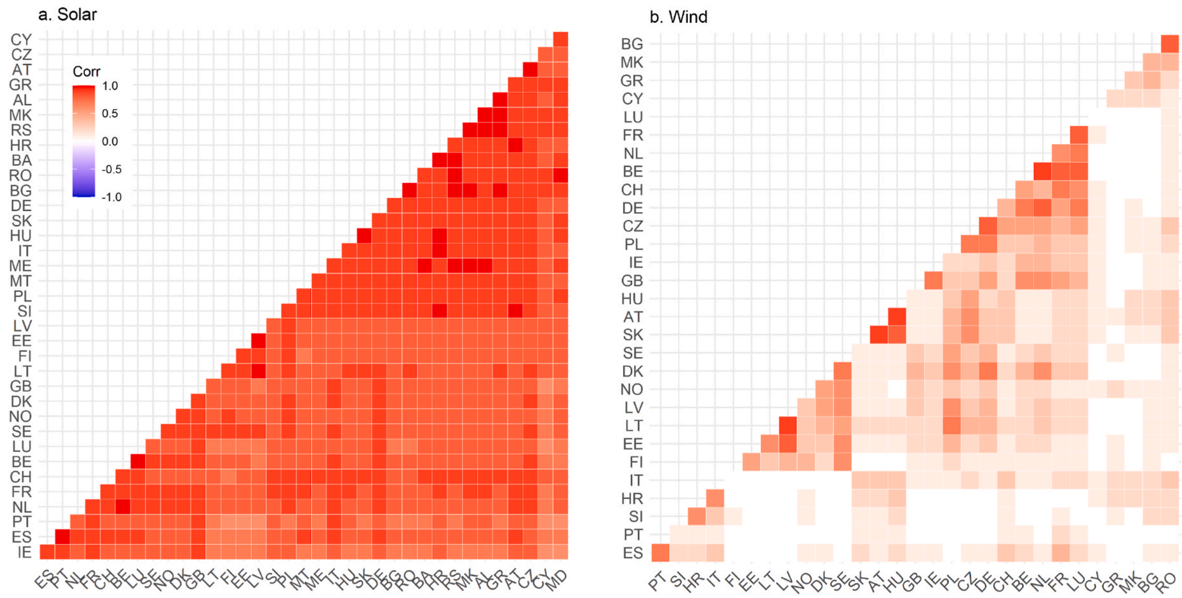

Fig. 5. Correlation of solar (a) and wind (b) capacity factors between countries.

pacities per country and technology. We can build an efficient frontier with all the portfolios with the minimum possible SD for each attainable CF. By comparing this efficient frontier with each country's CF and SD in autarky, we can quantify the potential benefits of combining technologies and integrating the VRE generation profile of different countries in terms of higher generation per unit of installed capacity (CF) and lower variability (SD). Within this frontier, the technical optimum is the portfolio with the highest possible CF per unit of variability (SD), or equivalently, with the lowest possible coefficient of variation ($CV = SD/\overline{CF}$). This method has the advantage of being simple and requiring only hourly CF data. For this reason, this method can easily be applied to other locations and at different resolutions as long as CF data are available. We focus on Europe because of its potential to integrate a continental-scale electricity grid [54], but similar approaches have also been applied in other countries (see Table 1).

Once we have calculated the efficient portfolios, we calculate their LCOE as the average of wind and solar costs weighted by their shares in the portfolio with the simplified LCOE formula:

$$LCOE = \frac{CRF \cdot IC + O\&M}{8760 \cdot CF}$$

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1}$$

where the capital recovery factor (*CRF*) is the ratio (depending on the interest rate *i* and the period of the investment *n*) by which we multiply the total installation cost (*IC*) to obtain the annualized capacity cost. The numerator of the LCOE is therefore the total average annual cost, including the annualized capacity cost (*CRF·CC*) and the fixed operation and maintenance cost (*O&M*), and its denominator is the annual generation, i.e. the number of hours of the year multiplied by the average CF.

For the LCOE calculation, we assume a capacity cost of 790 \$/kW for solar and 1540 \$/kW for wind and a fixed annual operation and maintenance cost of 11.4 and 39.1 \$/kW per year for solar and wind, respectively. These values correspond to the 2020 costs for photovoltaics and wind onshore according to the IEA Net Zero report [12]. We assume a 5% interest rate and 25 years lifetime and the same costs across countries and for both current and future scenarios. Whereas this is a simplification of reality, it helps us identify the benefits provided by wind-solar complementarities excluding all other factors. Assuming the same costs for both current and future scenarios overestimates the LCOE of the future portfolios, as VRE costs are expected to decline, but isolates the effect of the improvements in CF and SD and the optimization process from overall cost trends and potential prediction errors if we included future cost projections.

4.2. Research design

The combination of high temporal (hourly for 30 years), spatial (country-level for Europe) and technological (wind onshore and offshore and solar) resolution of our dataset allows us to study how different strategies optimize the CF-SD trade-off. First, we see the impact of aggregating capacities of the same technology across countries, with current data and also with the projected future evolution of wind power. Then we study the complementarity between wind and solar technologies, both within and across countries. To see the marginal benefits of increasing levels of integration, we define 3 incremental spatial configurations according to the evolution of the market coupling integration process in Europe. The Central West Europe (CWE) market coupling mechanism was launched in 2010 including the Benelux, France and Germany. In 2014, the North-Western Europe (NWE) system integrated CWE, Great Britain, the Nordics and the Baltics. The largest configuration is the pan-European, including all countries available in each dataset and labelled simply as "Europe".

We analyse these dynamics at three different temporal scales: hourly, daily and monthly. The hourly level is the most relevant because electricity supply and demand have to be balanced continuously to keep the grid's stability. Hourly resolution would capture the challenges posed by short-term intermittency (such as that caused by clouds for solar) and the diurnal cycle. Current energy storage technologies are well-suited to balancing this short-term variability, but the lack of economically-viable technologies with discharge durations above 24 h [8] makes the monthly timescale relevant, as it shows the seasonal complementarity between countries and technologies. Between these extremes we also consider the daily timescale, which removes the diurnal solar cycle and captures medium-term variability (i.e. windy vs calm and cloudy vs clear days). We mainly focus on the two extreme timescales: hourly and monthly and provide the daily-scale results in the appendix.

Finally, we will focus on the European Union in Section 5.3 (plus Great Britain because it is well connected to the continental electricity system and minus Cyprus and Malta for the opposite reason) to evaluate the potential benefits of spatial integration and deployment coordination to maximize capacity factor at the minimum possible variability. We compare the actual current installed capacities with those projected with the EU-reference scenarios, and with the current and future optimal portfolios according to the mean-variance framework outlined above.

5. Results

5.1. Spatial integration of individual technologies across countries

First, we evaluate the potential benefits of integrating the generation patterns of a single technology across countries. We present the results for wind and solar technologies, for hourly and monthly timescales, and for estimates of both current and future CF for wind. Fig. 6 shows the efficient frontiers for three increasing spatial configurations: Central West Europe (CWE: Benelux, France and Germany), North-Western

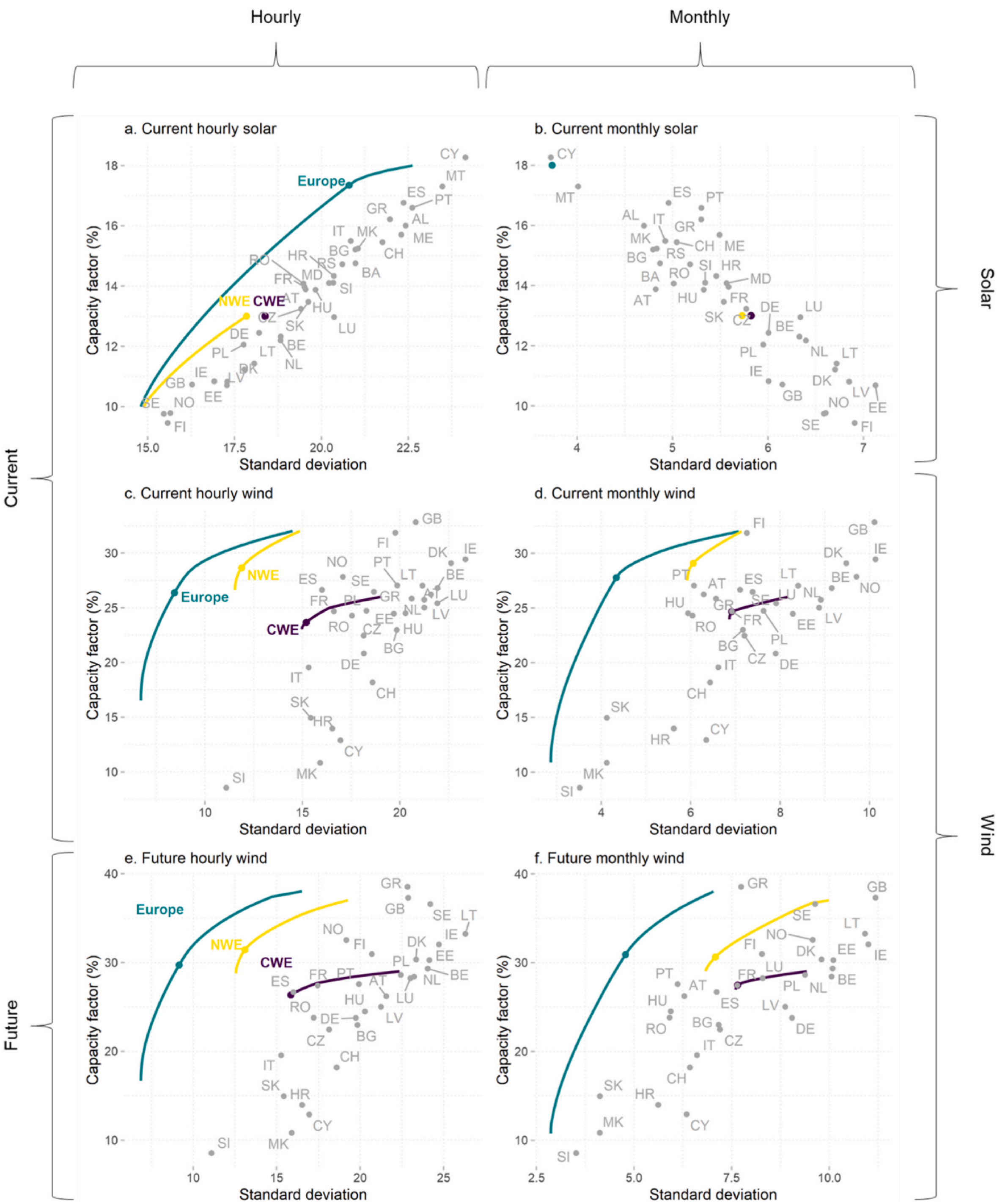

Fig. 6. Efficient frontiers (lines) and optimal portfolios (highlighted point on each frontier) for solar (a–b) and wind (c–f) compared to countries in autarky. Current (a–d) and future (e–f) timeframes at hourly (a, c, e) and monthly (b, d, f) timescales. Note that the vertical axes are different for each row and the horizontal ones for each figure. See Figure A1 for daily timescale. CWE: Central West Europe. NWE: North-Western Europe.

Europe (NWE: CWE, the Nordics and the Baltics), and Europe (full dataset comprising the individual countries shown on each of the figures). Each of the lines represents the efficient frontier for each spatial configuration, i.e. the set of portfolios (shares of installed capacities per country) that have the minimum possible SD for each attainable mean CF. Each of the grey dots represents one country in autarky, i.e. the expected CF and SD of the specific technology in each country. The frontiers representing larger geographical areas tend to lay to the left and above the smaller configurations and the autarky points, representing lower variability and higher capacity factors, respectively. The highlighted point on each frontier represents the optimal portfolio, i.e. the shares of installed capacities per country that minimize the coefficient of variation ($SD/\overline{CF}$).

Fig. 6a shows the potential benefits of solar integration across countries at the hourly timescale. Because the generation pattern of solar is more homogeneous across countries, all the autarky points representing individual countries are close to each other, compared to the situation of wind (Fig. 6c), where the frontiers are farther apart from the autarky points, representing higher complementarities. If we drew a regression line on the hourly solar autarky points (Fig. 6a), the coefficient of determination would be much higher than for wind, and the position of each country along the regression line would be easily predictable with the higher latitude countries at the bottom-left with low CF and SD, and low latitude countries at the top-right with higher CF and SD at the hourly level. For these reasons, the benefits of solar spatial integration and deployment coordination, which are illustrated by the movement of the efficient frontiers left and upwards with respect to the autarky points, are limited even in the largest configuration including all of Europe.

Whereas the correlation between CF and SD is usually positive, this relationship reverses for the case of solar at the monthly timescale (and also daily, see Appendix Figure A1). At hourly timescale, the countries with higher solar resource have higher peak generation at noon and zero at night, which explains the higher SD as the CF increases towards the equator. At the monthly level, however, countries with better solar resource generate more across all seasons and have lower seasonality towards the equator, giving lower variability compared to northern countries. For this reason, integrating solar across countries within the same hemisphere does not provide much benefits because all capacity would be allocated to the countries with the best resource, as they are better both in terms of higher CF and lower seasonal variability.

Fig. 6c–d shows that the integration of wind resources across countries can provide potential benefits compared to each country in autarky due to the more heterogeneous generation patterns across countries (Fig. 5b). Additionally, the future projections for wind make spatial integration even more critical as the CF and consequently SD are expected to increase in the future (not necessarily the coefficient of variation if CF increases faster than its SD). The shape and magnitude of the future frontiers shed light on the increasing potential benefits of integration as CF and SD increase.

As an example of how to interpret these figures, we can see that e.g. countries such as Spain, Sweden or Belgium have a similar expected wind CF in autarky to the optimal European portfolio for current wind (Fig. 6c). However, the optimal European portfolio can achieve that level of expected CF at only a fraction of the variability (SD) of any of these countries in autarky. This entails that the integration costs caused by variability would be lower in the optimal portfolio than the aggregation of the integration costs caused by variability in each country in autarky.

Whereas the highlighted points along the efficient frontiers represent the technical optima (i.e. the minimum coefficient of variation), decision-makers could favour other locations along the frontiers depending on the preferences regarding capacity allocation across countries and the cost of renewable capacity, transmission and alternative options for providing flexibility to mitigate output variability. Each point along the frontier represents different shares of installed capacities per country. The points towards the top of the frontier will tend to concentrate capacities in the countries with the highest CF (the extreme case, the highest CF portfolio is just 100% of the capacity installed in the country with the highest CF), whereas the portfolios towards the bottom of the frontier will tend to favour lower variability and thus the combination of countries with the most different generation patterns that can offset each other and therefore provide a more stable aggregate generation profile.

In summary, these results confirm that (i) the integration of wind resources across countries provides more potential benefits than the integration of solar, (ii) the benefits of integration arise at all timescales from hourly to monthly, and (iii) the benefits of integration will become more relevant in the future as both CF and SD increase.

5.2. Solar-wind complementarity within and across countries

In this section, we further disaggregate wind into onshore and offshore, to see potential complementarities between these two types of wind and solar in improving the CF-SD trade-off. First, we optimize the share of each of the three technologies in autarky for the selection of countries shown in Fig. 7. Then we calculate the efficient frontiers and optimal portfolios with the same geographical configurations as in the previous section at both hourly and monthly timescales (daily results in the appendix).

The grey points in Fig. 7a and c represent the CF and SD of the optimal portfolio of technologies for each country in autarky at hourly and monthly timescales, respectively, and Fig. 7b and d shows the corresponding shares of each technology per country. At the hourly timescale, the solar share is similar for the selected countries, within a range of 38–45% of the total. The remaining capacity is allocated to onshore and offshore wind, except in the Netherlands and Denmark, where offshore dominates and onshore does not have any installed capacity. At the monthly timescale, the share of solar is also similar across countries, but generally higher (∼50–65%) than at the hourly level. At a monthly timescale, offshore mostly displaces onshore wind. At the daily timescale (Figure A2 in the Appendix), the shares of solar are even higher (∼68–75%). In general (i.e. across the studied countries and timescales), there is a complementarity between wind and solar that, when deploying capacities at optimal levels, may help mitigate variability and thus integration costs. These results also confirm that the benefits of spatial integration are higher for the hourly than for the monthly timescale (shown by the fact that the autarky points are farther away from the efficient frontiers in the hourly than in the monthly figures). These results also show that integrating resources across countries (the frontiers) provides better results than countries in autarky (grey points), even when the shares of each technology are optimized. More importantly, because the optimal shares of each technology are similar across timescales, the combination of wind and solar capacities helps mitigate variability at the three timescales simultaneously.

5.3. European Union

The European Union (EU) has been developing a joint energy strategy since the first Energy Union communication (COM/2015/080) in 2015. As a result, electricity markets are becoming more integrated and countries are coordinating their policies towards decarbonization. In this context, the EU can further benefit from the coordination of VRE installed capacities to optimize the trade-off between high capacity factors and low variability, consequently reducing both levelized and integration costs.

In this section, we compare the efficient frontiers and optimal portfolios at the hourly timescale for the current and future expected wind and solar generation profiles with the actual current installed capacities and the planned wind and solar installed capacities according to the EU Reference scenarios. For our purposes in this section, we include the 27

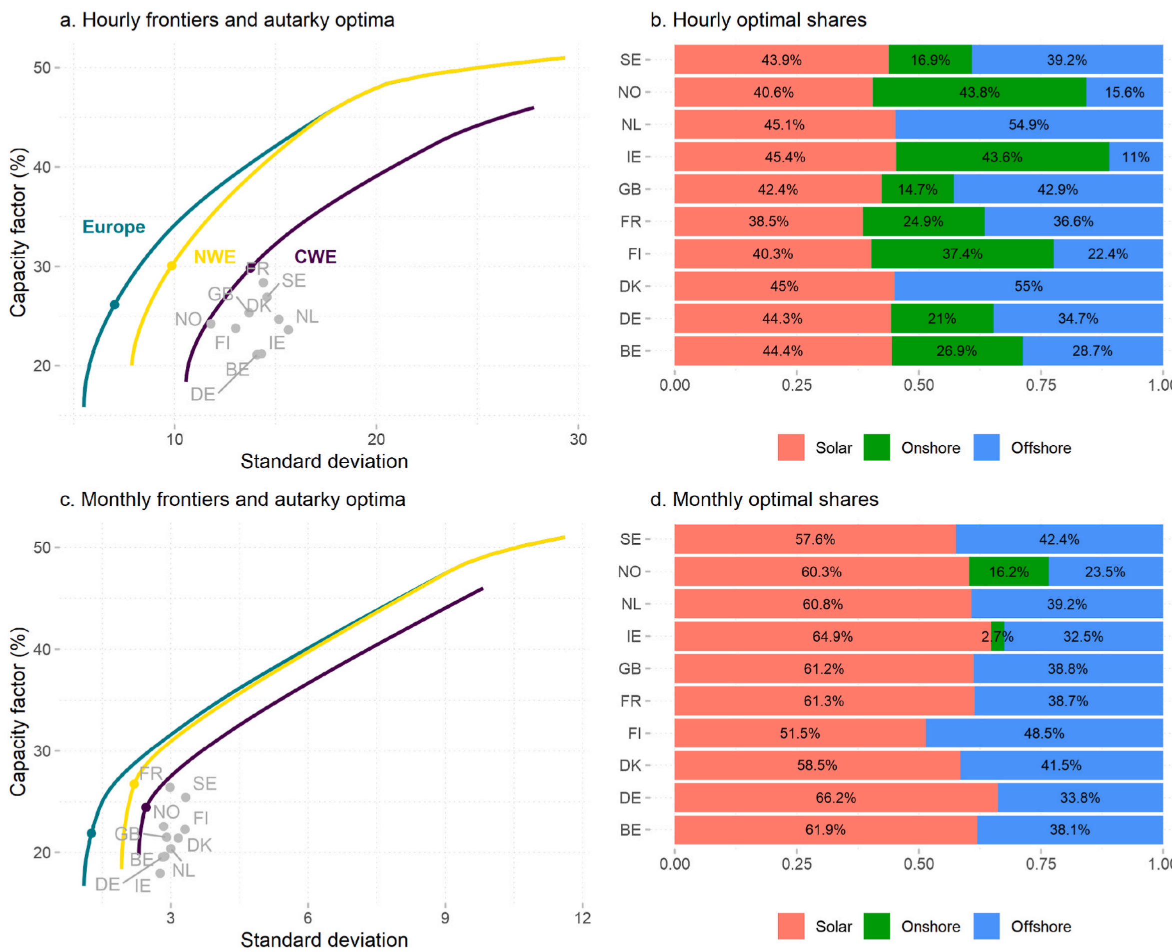

Fig. 7. (a) Efficient frontiers (lines) and optimal portfolios (highlighted point on each frontier) including wind onshore and offshore and solar, compared to selected countries optimizing technological shares in autarky at the hourly timescale. (b) Optimal share of each technology for each of the selected countries in autarky. Panels (c) and (d) are equivalent to (a) and (b) at the monthly timescale. See Figure A2 for the daily timescale. CWE: Central West Europe. NWE: North-Western Europe.

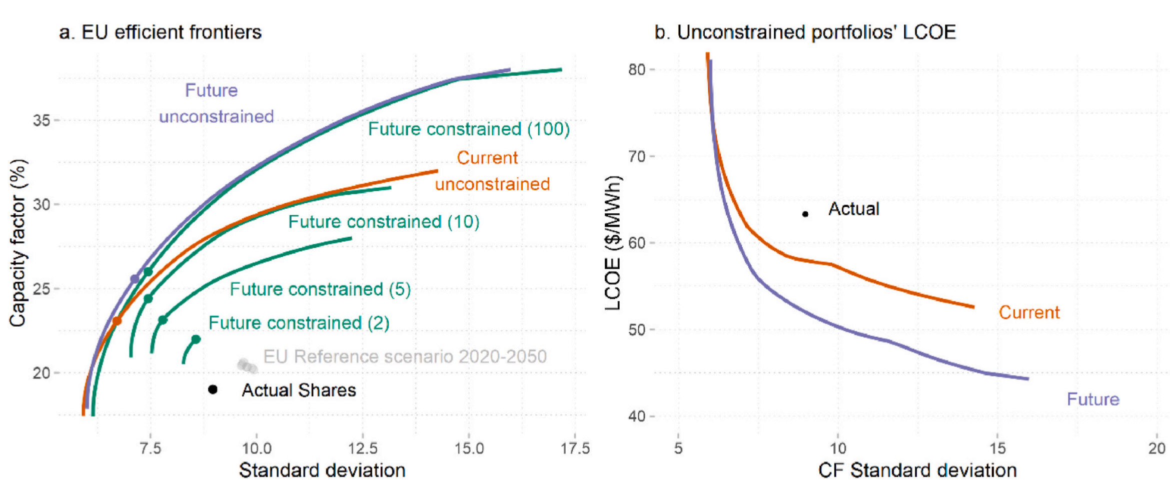

Fig. 8. (a) Efficient frontiers and optimal portfolios for deploying wind and solar power through Europe. Efficient frontiers are shown as lines and optimal portfolios are highlighted as a point on each frontier. Labels for each frontier indicate whether they use current or future capacity factors, and numbers in brackets indicate the capacity constraint (maximum/minimum capacities are the actual installed capacities multiplied/divided by the number in brackets, respectively). For comparison, the actual shares in 2020 and in the EU reference scenarios between 2020 and 2050 (each 5 years) are shown as grey points. All portfolios consider the EU-27 including Great Britain and excluding Malta and Cyprus. Frontiers for the levelized cost of electricity (panel b) show the unconstrained current and future scenarios compared to the actual distribution of installed capacities.

EU members excluding Malta and Cyprus for their negligible interconnection with the continent, and including Great Britain for the opposite reason. We will refer to this set of countries as the "EU" from now on. Because we do not have future solar data, solar capacity factors are assumed to remain the same as the current ones.

Fig. 8a shows that with actual current (2019) wind and solar installed capacities across countries and using the simulated hourly CF data described above, the average CF of the aggregate EU VRE generation profile is 19% with a SD of 9%. The installed capacities projected in the EU reference scenarios between 2020 and 2050 (every 5 years) do not seem to consider the potential complementarities between countries and technologies in their planning, as they do not improve the CF-SD trade-off. Both the CF and SD of the EU reference scenarios are slightly higher (~20% CF and ~10 SD) than the actual current shares. However, optimally deploying wind and solar installed capacities across countries could achieve an aggregated generation profile that improves the actual situation both in terms of a higher CF (23.1%) and lower SD (6.7%).

In summary, the integration of electricity systems across Europe and the deployment coordination of VRE installed capacities according to their complementarities has the potential to increase the expected CF by 21.6% (4.1 percentage points) compared to the current situation and at the same time reduce generation variability (SD) by 25.6% (2.3 percentage points). This would significantly reduce system costs by lowering both levelized cost of generation (given the higher CF, assuming the same installation costs across countries) and integration costs (due to lower variability). In the future, the potential benefits of spatial integration and deployment coordination will be even higher due to increasing CF and SD. The optimal future portfolio could reach a CF of 25.6% with a SD of 7.3%.

By comparing the LCOE of a system with the actual current VRE installed capacities (black point in Fig. 8b) with the LCOE curves of the efficient frontiers, we can see the potential cost reduction of optimally deploying VRE capacities in the EU. The system cost is the sum of LCOE and integration costs. Integration costs are determined by wind and solar variability, but they are not straightforward because they depend on the capacity of the system to integrate variability (e.g. flexible capacity, demand response, available storage, etc.). For this reason, we illustrate LCOE in the vertical axis in relation to variability in the horizontal axis, which may be interpreted as a proxy for integration costs. Quantifying the relationship between variability and integration cost would allow us to identify the economic optimum that minimizes the system cost beyond the technical optimum that maximizes the CF per unit of variability (i.e. minimizes the coefficient of variation).

The optimal portfolios that maximize the CF per unit of variability (or equivalently minimize the coefficient of variation) are not usually feasible due to all kinds of real-life constraints, such as imperfect cooperation, political preferences regarding the distribution of installed capacities, capital constraints, etc. For these reasons, Fig. 8a also depicts a potential pathway by showing the future efficient frontiers and optimal portfolios constraining maximum and minimum installed capacities per country and technology departing from the actual current shares of VRE installed capacities per country and progressively relaxing the constraints until the final unconstrained future portfolio. The constraints are built such that the maximum relative installed capacity (i.e. the maximum asset's weight in the portfolio) per country and technology is the actual current capacity multiplied by a constant, and likewise the minimum is the current actual capacity divided by the same constant. For instance, for a constant of 2, the maximum share of each technology-country installed capacity is twice the actual current share, and the minimum would be half as much. We do this for the values of 2, 5, 10, and 100. This shows that the efficient future portfolios would need to have a radically different distribution of VRE installed capacities across countries from the actual current distribution.

Fig. 9 shows the actual current installed capacities per technology and country (panel a, only shares >0.8% shown), compared to the shares in the current optimal (b) and the future optimal (c) portfolios. The main difference between actual and optimal portfolios is that whereas Germany has the highest share of VRE installed capacity in the EU with more than a third, Finland would be the country with the highest VRE shares in both the present and future optimal portfolios with high shares of both wind and solar. Spain has high VRE installed capacity, and would still play a main role in the current optimal portfolio, but it would be substituted by Greece in the future. Portugal, Romania and Great Britain have high VRE shares in both the current and future optimal portfolios.

Whereas solar capacities dominate the autarky optima (Fig. 7), wind capacities account for about 80% of the total in the optimal European configurations (Fig. 9). This is because wind patterns are more heterogeneous across countries than solar (Fig. 5), so the allocation of wind capacities across locations with complementary patterns provides more benefits than combining similar solar patterns. These results, however,

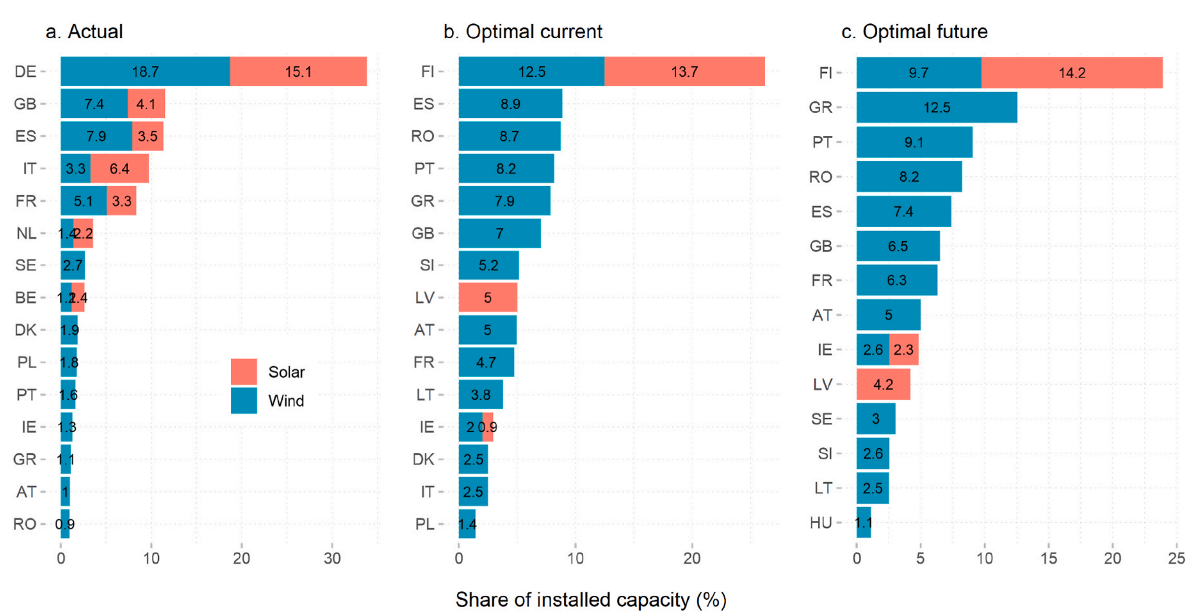

Fig. 9. Shares of wind and solar per country: actual current installed capacities (a), optimal shares in the current (b) and future (c) scenarios.

represent only the technical optima solving the trade-off between capacity factor and variability. Economically optimal capacity shares in real life would differ due to the different cost between technologies and countries as well as the inclusion of additional evaluation criteria, such as transmission and storage costs and availability, etc.

5.4. Limitations

As the main goal of this study is to evaluate the complementarity between VRE technologies, the main limitation derives from the simplicity of the mean-variance framework, which only takes into account CF and SD as the relevant variables for capacity optimization. This simplicity allows us to uncover the potential benefits of VRE integration in the spatial, temporal and technological dimensions, but provide theoretical results that are not necessarily optimal when other relevant factors, such as the availability of dispatchable technologies, the potential of demand flexibility or the cost of interconnection are taken into account. Additionally, because we assume the same installation costs across countries, our results show the potential benefits of integration and coordination across countries, but not the optimal capacity shares defined from a financial perspective, as that would require using real-world installation cost data which are not openly available. For a more comprehensive analysis, investment and dispatch models may provide more relevant insights of actual electricity systems. Further research could integrate additional factors, such as interconnection costs or constraints, into the mean-variance framework.

Another limitation is related to the feasibility of such large interconnections. While it may be difficult to expand transmission lines, the European Union is advancing towards a unified electricity market and has the objective of reaching 15% of interconnection capacity by 2030 [54]. For this reason, even though there are implementation challenges, Europe is particularly well suited to achieve the first continental-scale electricity grid that could allow large scale integration and coordination among its members.

6. Conclusions

In this paper we develop a general framework for assessing the benefits of integrating renewable electricity generation across regions and different technologies. We use this framework to optimize the trade-off between achieving high generation output (and thus lower costs per unit of electricity), and low generation variability (and thus lower system integration costs). We quantify the potential gains of spatial integration and deployment coordination across countries by identifying the portfolios of wind and solar installed capacities across countries that minimize variability for each attainable level of capacity factor, and then find the optimal portfolio that provides the maximum capacity factor per unit of variability (i.e. that minimizes the coefficient of variation).

We find that the integration of solar resources across countries has limited benefits due to the homogeneity of solar generation within regions in the same hemisphere. However, due to the more location-specific nature of wind patterns, the integration of wind resources can provide significant benefits. Optimally allocating the installed capacities of wind and solar across countries can bring substantial benefits in terms of higher capacity factors and lower variability. The optimal portfolio of wind and solar installed capacities across countries could improve the aggregate expected capacity factor by 21.6% (from 19% to 23.1%) and reduce its hourly variability by 25.6% (standard deviation declines from 9% to 6.7%) in the European Union (including Great Britain and excluding Cyprus and Malta).

Because we provide efficient frontiers in addition to the single optimal portfolio, and in relation to the autarky situation of each country individually, this framework allows us to evaluate near-optimal solutions that are more feasible in the real world. We also provide the technical benefits in terms of higher capacity factors and lower variability and economic benefits in terms of lower levelized cost in relation to variability, which is a proxy for integration cost. This framework could be extended by endogenizing costs into the optimization process and integrating the relationship between variability and integration cost to achieve the ultimate goal of minimizing system cost of high-penetration variable renewables electricity systems. As wind and solar will soon become the largest sources of electricity production both within Europe, and then worldwide, this framework can help identify the optimal combination of resources that maximize production and minimize variability, contributing thus to a faster and cheaper decarbonization process.

Author contributions

Javier López Prol: Conceptualization, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Visualization, Supervision, Project administration.; Fernando de Llano Paz: Conceptualization, Writing - Review & Editing.; Anxo Calvo Silvosa: Conceptualization, Writing - Review & Editing.; Stefan Pfenninger: Resources, Formal analysis.; Iain Staffell: Resources, Formal analysis, Writing - Review & Editing.

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.

Data availability

Data and code are available on 10.5281/zenodo.7878958.

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Appendix

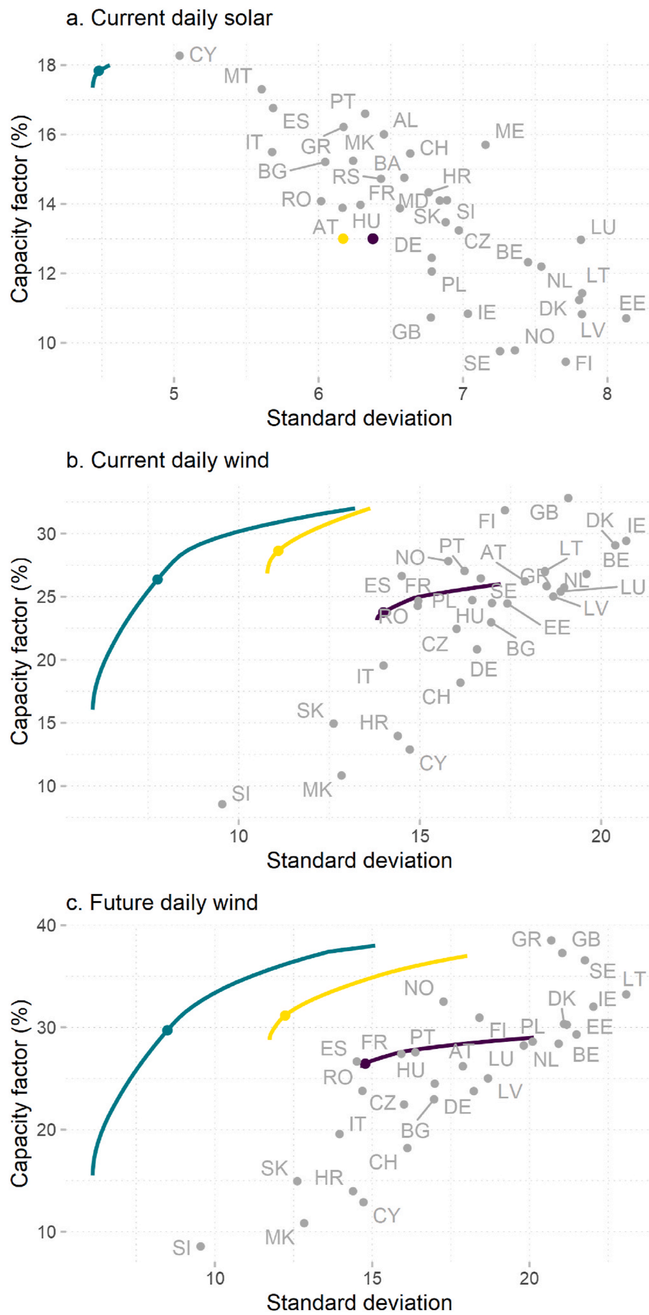

Fig. A.1. Equivalent to Fig. 6 at daily timescale.

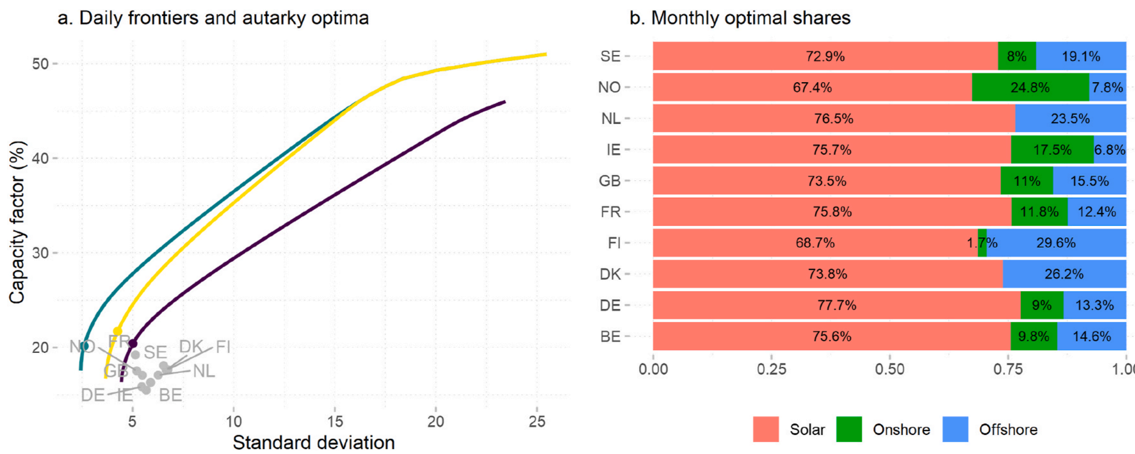

Fig. A.2. Equivalent to Fig. 7 at daily timescale.

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