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Optimal wind-solar energy mix in Italy: Impact of climate variability

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Abstract

In the context of the 2009 EU directive promoting the use of energy from renewable sources, Italy has reached its 2020 target of a 17% share of renewables in the final energy consumption 6 years in advance. In this study, we evaluate the existing renewable energy mix in Italy at regional scale by comparing it to an optimized mix taking into account climate variability and allowing full decommissioning of the currently installed plants. The variability of the production and of the demand over the 1989–2012 period is resolved by plugging regional climate simulations of this period into a model simulating the renewable energy production as well as the Italian electrical consumption at regional scale. The optimal mix is then inferred from a mean-risk analysis with as objectives both to maximize the mean of the total renewable production and to minimize the variance, or risk, of the latter. We consider two cases: in the first one the analysis takes cross-region correlations in the production and the demand into account and in the second one the analysis is local to each region. The optimal mix maximizing the ratio of the total mean penetration over the total risk for the same renewable capacity as installed in 2015 consists of about two thirds wind and one third solar, i.e. twice as much wind as the actual 2015 Italian renewable mix. The spatial distribution also differs significantly from the actual mix and from what would be obtained ignoring the risk and low-frequency climate variability.

Keywords: Energy, Renewable, Climate, Variability, Mediterranean

14 **Highlights**

- 15 • Taking into account the risk strongly impacts the optimal Italian re-
16 newable mix.
- 17 • The risk should account for climate variability from hours to decades.
- 18 • The actual Italian mix could yield a higher renewable penetration at a
19 lower risk level after geographical optimization.

20 **1. Introduction**

21 The world net electricity generation is expected to increase by 45% be-
22 tween 2015 and 2040 (IEA, 2017). In view of climate change and energy
23 security concerns, the renewable energies will inevitably play a major role in
24 satisfying this growing demand. Non-hydropower Renewable Energy Sources
25 (RES) are the fastest-growing energy sources for new generation capacity and
26 their share is expected to grow from 7% of total world generation in 2015
27 to 15% in 2040, with more than half of this growth coming from the wind
28 power (IEA, 2017).

29 However given the variable nature of the RES production and the need
30 for a constant supply-demand balance, increasing penetration of renewables
31 raises structural, technological and economical issues. On one hand, variabil-
32 ity may lead to local power shortages or increased transmission congestion.
33 This must be compensated at all times by an increased flexibility of the
34 conventional generation systems such as coal plants or combined cycle gas
35 turbines (Huber et al., 2014). On the other hand, it brings higher price insta-
36 bility along with a reduction of the wholesale prices. In the long run falling
37 prices may ‘erode’ the returns of both renewable and conventional producers,
38 eventually pushing the latter out of the market while they are essential to
39 smooth out the fluctuations of renewable power output and ensure system
40 stability. Thereby the possibilities for a future large-scale renewable capacity
41 are limited (Hirth, 2013; Spiecker and Weber, 2014).

42 Technological and spatial diversification are possible strategies to circum-
43 vent the problem of intermittency. In Europe, wind and solar-generated
44 electricity roughly have negatively correlated seasonal cycles, solar genera-
45 tion being maximal in summer and wind generation in winter (Heide et al.,

46 2010). Spatial diversification is only applicable at large scale, whenever the
47 RES variability is sufficient (see Widén (2011) for a study focusing on Swe-
48 den and Tsuchiya (2012) analyzing Japan). In light of those considerations,
49 questions can be asked about how to implement this double strategy of di-
50 versification.

51 Technological and geographical optimization of renewable energy systems
52 within a multi-objective framework has been discussed by several authors at
53 continent and country scales. Complete electrical systems have been designed
54 to quantify the requirements in installed power, transmission grid and storage
55 capacity for a 100% of renewable energy scenario over Europe. For example,
56 at the European scale, Heide et al. (2011) optimize the wind/solar mix in
57 a fully renewable future European power system to reduce the storage and
58 balancing needs; Rodríguez et al. (2014) do the same for the cross-border
59 transmission capacities in the future; and Becker et al. (2014b) investigate
60 the change in the optimal wind/solar mix in Europe as the transmission grid
61 is enhanced. Becker et al. (2014a) optimize the wind/solar mix in the US
62 to reduce storage needs and Nelson et al. (2012) simulate how a range of
63 generation technologies, storage and transmission may meet the projected
64 energy demand in the US at the least societal cost. Finally, Elliston et al.
65 (2012) analyze how the Australian renewable mix should change in order
66 to reduce the need for backup generation; and Lund and Mathiesen (2009)
67 discuss feasible energy mix scenarios for a fully renewable electricity supply
68 in Denmark.

69 Other conceptual frameworks with less ambitious energy targets have
70 been explored at continental and regional scale by repowering the current
71 installed renewable energy capacity. Repowering consists in fully decommis-
72 sioning current renewable energy capacity and in re-allocating this capacity
73 according to specific objectives (Del Río et al., 2011). For example, Bel-
74 tran (2009) applies the mean-variance optimization techniques to infer the
75 optimal energy mix; Roques et al. (2010) use similar methods to determine
76 optimal wind power deployment among 5 European countries; Thomaidis
77 et al. (2016) and Santos-Alamillos et al. (2017) use mean-variance optimiza-
78 tion to assess the optimal wind and solar deployment and repowering actions
79 in Spain. These studies use the Markovitz mean-variance portfolio theory or
80 analogous methodologies to define the optimal full re-allocation of existing
81 power plants among regions. It relies on a trade-off between maximizing
82 the mean renewable productivity while minimizing the aggregate renewable
83 energy supply risk (i.e. variability).

84 The majority of assessments of the optimal renewable energy mix are
85 based on the statistical properties of the historical production and demand.
86 Due to the only recent deployment of wind and solar energy systems the
87 length of regional production and demand time series is often limited to a
88 few years, which is not sufficient to properly take into account the effect of
89 multi-annual climate non-stationarity at time scales of the life cycle of a wind
90 and solar farm ($\sim 30y$) and reliably estimate statistics such as the mean and
91 the covariance of the production.

92 In this article, we develop a methodology to analyze the repowering strate-
93 gies of wind and solar plants in Italy and evaluate the current renewable mix.
94 We determine the optimal geographical distribution of each renewable energy
95 source using a mean-variance optimization. In addition to focusing on a dif-
96 ferent region than the aforementioned studies, our work presents the following
97 important methodological novelty. Models of electricity generation and con-
98 sumption are designed to feature climate variables such as the wind speed,
99 the solar irradiance and the temperature. These variables are taken from a
100 hindcast of the 1989–2012 period over the Mediterranean region (Fig. 1b). In
101 this way, our mean-variance analysis — and additional statistical diagnostics
102 such as the frequency of occurrence of shortage and saturation situations —
103 takes into account the impact of interannual to intraday climate variability
104 on the renewable production and the demand. Applying the model to Italy,
105 we show that resolving such a large spectrum of time scales is essential to
106 design a renewable energy system that remains optimal over its full life cy-
107 cle. By replacing the hindcast simulations with future climate projections
108 it is possible to use our methodology to study the impact of future climate
109 evolutions including antropogenic climate change on the optimal renewable
110 mix, however this is left for further research.

111 Italy offers an interesting case study of a market with high renewables
112 penetration as it has reached its quota of 17% renewables in final energy
113 consumption in 2014, therefore implementing the 2009 Climate Package six
114 years ahead of the 2020 horizon (GSE, 2015). This is the result of ambitious
115 support policies for RES development that have generated and still subsidize
116 a significant amount of new investments, notably in solar and wind power
117 plants.

118 The analysis of the Italian renewable mix is based on wind and solar
119 photovoltaics (henceforth PV) production and electricity consumption com-
120 puted from a regional climate simulation performed in the framework of two
121 international programs — the Hydrological Cycle in the Mediterranean Ex-

122 periment (HyMex Drobinski et al., 2014) and the Coordinated Downscaling
123 Experiment for the Mediterranean (Med-CORDEX Ruti et al., 2016). Two
124 cases for the optimization of the renewable energy mix are investigated: in the
125 first case, the Italian electrical network is considered as unique and the over-
126 all mix is optimized; in the second one, each interconnected zone minimizes
127 its own risk in priority, ignoring potential benefits from taking covariance
128 and interconnection between zones into account.

129 This article gives a first proof of concept that it is possible to design
130 optimal renewable energy mixes taking into account climate variability over
131 a large range of temporal scales. The remainder of the paper is structured
132 as follows. Section 2 details the datasets, the simulation and the produc-
133 tion and demand models on which is based the analysis of the optimal mix.
134 The mean-variance optimization problem and its mathematical properties are
135 presented in Section 3. In Section 4 we calculate the optimal geographical
136 distribution of wind and solar generation in Italy and analyze the properties
137 of these mixes in terms of weight given to each technology and in terms of
138 occurrence frequency of shortage and saturation situations. The impact of
139 climate variability on the optimal mixes is discussed in Section 5, together
140 with their comparison with the actual wind-solar mix in Italy. In Section 6
141 we draw conclusions. The robustness of the numerical results to the climate
142 data, the sampling and the model is tested in SI-1.

143 **2. Data**

144 *2.1. GME and GSE databases*

145 Time series of the hourly Italian regional electricity demand and of the
146 yearly regional renewable capacity factors are used to design the demand
147 and generation models. These variables are extracted from two publicly
148 available databases provided respectively by the market operator GME¹ and
149 the energy operator GSE². For this reason, we first briefly comment on the
150 structure of the Italian electricity market and next describe the databases
151 we use.

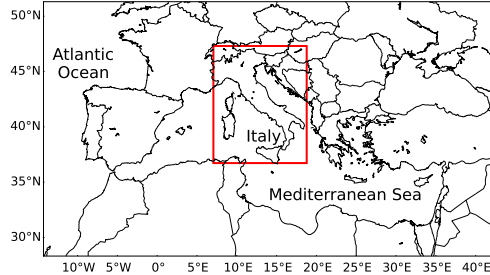
152 The Italian power market consists of 7 foreign virtual zones, 6 regional
153 sub-markets, or bidding zones, and 5 poles of limited production. The 20

¹ Gestore del Mercato Elettrico: <https://www.gse.it/dati-e-scenari/statistiche>

²Gestore dei Servizi Energetici: <https://www.gse.it/dati-e-scenari/statistiche>



(a) Italian electrical regions.



(b) Domain of the HyMeX/MED-CORDEX simulation covering Europe and the Mediterranean region. The rectangle indicates the domain of investigation of this study.

154 administrative regions composing the Italian territory are aggregated in the
 155 6 bidding zones (Fig. 1a): Northern Italy (NORD), Central-Northern Italy
 156 (CNOR), Central-Southern Italy (CSUD), Southern Italy (SUD), Sardinia
 157 (SARD) and Sicily (SICI). Each zone has its own generation mix determined
 158 by historical and geographic reasons and characterized by a given level of
 159 efficiency. For instance, the Northern regions have larger hydroelectric pro-
 160 duction due to the proximity to the Alps. Inter-zonal transmission capacities
 161 are not equally distributed either.

162 The Italian power exchange, which is managed by the GME³ is composed
 163 of a spot market, a forward market and a platform for the physical delivery
 164 of contracts concluded on the financial derivatives segment of the Italian
 165 Stock Exchange. The spot market is composed of three sub-markets: the
 166 day-ahead, the intraday and the ancillary services markets. We focus on the
 167 day-ahead submarket. The liquidity of the day-ahead market, calculated as
 168 the ratio of volumes traded on the day-ahead market to the total volumes
 169 (including bilateral contracts) of the Italian power system, has increased
 170 between 2010 to 2015, passing from 62.6% with 198 operators in 2010 to
 171 67.8% with 259 operators in 2015. The peak liquidity has been reached in
 172 2013 with a 71.6% liquidity and 214 operators (GME, 2017).

173 The GME database encompasses hourly bids and offers in the wholesale

³ The GME manage as well the OTC Registration Platform for forward electricity contracts that have been concluded off the bidding system.

174 electricity market from 2004 to 2017; the offers are identified by supplier’s
 175 technology. The hourly electricity demand is appraised from this source.
 176 GSE annual reports (e.g. GSE, 2016) contain information about the yearly
 177 electrical production and the associated installed capacity⁴ detailed by region
 178 and sources from the beginning of 2008 to the end of 2016. At the beginning
 179 of this period, the installation of renewable energy capacity has shown a very
 180 rapid increase.

181 The regional time-mean capacity factors for PV and wind are calculated
 182 from this source. Since 2013, the PV and wind capacity factors are relatively
 183 stable. The demand and the capacity factors for PV and wind for the 2013–
 184 2017 period are presented in Table 1.

Region	Electrical demand (GWh/day — %)	Capacity Factor (PV — Wind)
NORD	312.2 — 56.5	12.1 — 20.4
CNOR	50.4 — 9.1	13.3 — 19.2
CSUD	82.0 — 14.9	14.1 — 18.8
SUD	44.2 — 8.0	15.6 — 20.9
SARD	26.7 — 4.8	14.5 — 19.6
SICI	36.8 — 6.7	15.9 — 18.7

Table 1: Regional electrical demand (from GME) and capacity factors for PV (blue) and wind energy (green, both from GSE) averaged over the 2013–2017 period.

185 Table 2 summarizes the regional information on electrical installation —
 186 in particular the current installed capacity and transmission lines — at the
 187 end of 2015. In addition, Figure 2 represents the geographical distribution
 188 of the installed RES capacity. The PV (wind) installed capacity is 18.8 GW
 189 (8.9 GW). The Northern cross-border region contains the majority of the
 190 photovoltaic plants as well as the power lines. The Southern region has most of
 191 the Italian wind turbines and has the second transmission capacity, to foreign
 192 markets. Note that the electricity demand to Italy from other countries is
 193 not taken into account in this study. The share of the renewable energy
 194 production in the electricity demand over the six regions in 2015 is found to
 195 be 19.4%.

⁴In the GSE reports, the capacity for a particular year is the installed capacity at the end of this year.

Region	Transmission lines (MW)	PV installed capacity (MW)	Wind energy installed capacity (MW)
NORD	53400	8241	113
CNOR	4550	2256	133
CSUD	12720	2631	1582
SUD	34100	3600	4351
SARD	595	721	1001
SICI	10100	1302	1753

Table 2: Characteristic of regional electrical infrastructure based on GSE database.

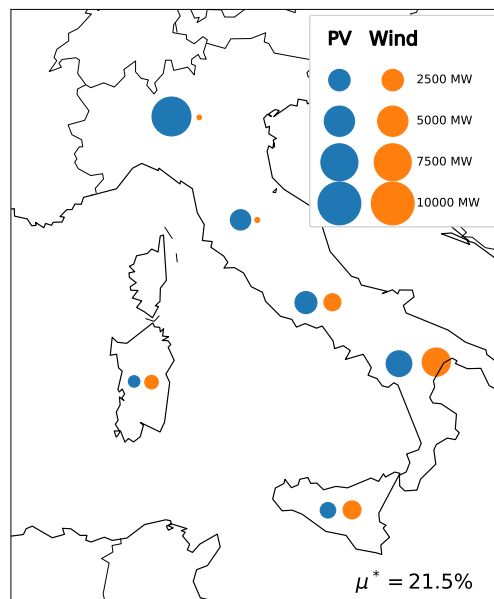


Figure 2: Geographical and technological distribution of the RES capacity installed by the end of 2015 in Italy (GSE database).

196 *2.2. Regional climate simulations*

197 A third variable employed in our study is the multi-year series of RES
198 production. The deployment of RES capacity being relatively recent (starting
199 around 2008 in Italy), available time series of observed RES production are
200 not sufficiently long to estimate statistics taking into account low-frequency
201 climate variability. To take into account climate variability, RES production
202 is instead computed using regional climate simulations covering the historical

203 1989 to 2012 period.

204 We use the version 3.1.1 of the Weather Research and Forecasting Model
205 (WRF). WRF is a limited area model, non-hydrostatic, with terrain following
206 eta-coordinate mesoscale modeling system designed to serve both operational
207 forecasting and atmospheric research needs (Skamarock et al., 2005). The
208 WRF simulation has been performed in the framework of HyMeX and MED-
209 CORDEX programs with a 20 km horizontal resolution over the domain
210 shown in Fig. 1b between 1989 and 2012 with initial and boundary condi-
211 tions provided by the ERA-interim reanalysis and updated every 6 hr (Dee
212 et al., 2011). The WRF simulation has been relaxed towards the ERA-I
213 large scale fields (wind, temperature and humidity) with a nudging time of
214 6 hr (Salameh et al., 2010; Omrani et al., 2013, 2015). A detailed description
215 of the simulation configuration can be found in e.g. Flaounas et al. (2013).

216 The simulation has been evaluated against ECA&D gridded precipitation
217 and precipitation at the Mediterranean basin scale (Flaounas et al., 2013),
218 and have been used to study heatwaves (Stéfanon et al., 2014; Chiriaco et al.,
219 2014), heavy precipitation (Lebeaupin Brossier et al., 2013, 2015; Berthou
220 et al., 2014, 2015, 2016) and offshore wind energy potential assessment (Om-
221 rani et al., 2017) in a configuration coupled or not with a regional ocean
222 model for the Mediterranean Sea (Drobinski et al., 2012). The simulation is
223 available on the HyMex/MED-CORDEX database⁵.

224 In the following sections, we describe the models used to estimate the
225 wind and solar production and the electricity demand from the daily climate
226 data. A large fraction of the variance of the production and of the demand is
227 contained in shorter periods than a day and significantly impact the results
228 of the mean-variance analysis (see SI-1). The production and demand models
229 thus all include a parameterization of the intraday variability.

230 *2.2.1. Electricity production model*

231 To compute wind energy production simulated daily-mean horizontal
232 wind-speeds are interpolated at hub height (101 m) using an empirical power-
233 law with exponent 1/7 (Justus and Mikhail, 1976). A transfer function based
234 on the power curve of a particular wind turbine, the relatively representative
235 Siemens SWT-2.3 MW-101m, is applied to the wind speed to compute the

⁵ <ftp://www.medcordex.eu/MED-18/IPSL/ECMWF-ERAINT/evaluation/r1i1p1/IPSL-WRF311/v1/day/>

236 electrical production at each climate-data gridpoint (Omrani et al., 2017)⁶
 237 Before applying the transfer function, the wind speed at hub height is mul-
 238 tiplied by a factor $(\rho/\rho_0)^{(1/3)}$ accounting for deviations of the daily-mean air
 239 density ρ from the standard density ρ_0 for which the power curve has been
 240 obtained. The air density ρ is computed from the air temperature, pressure,
 241 and specific humidity at the surface from the WRF dataset using the ideal
 242 gas law for moist air⁷.

243 In addition, it is essential in the mean-variance analysis to take intraday
 244 fluctuations of the wind production into account. In order to take into ac-
 245 count intraday wind fluctuations in the variance of the wind capacity factors,
 246 hourly realizations of the wind speed to be fed to the transfer function are
 247 obtained by randomly drawing samples from a Rayleigh distribution with
 248 mean given by the daily-mean speed at hub height. In other words, the wind
 249 magnitude $V(d, h)$ at day d and hour h at some gridpoint is drawn from the
 250 Rayleigh distribution

$$f(x|\sigma(d)) = \frac{x}{\sigma^2(d)} e^{-\frac{x^2}{2\sigma^2(d)}}, \quad x \geq 0 \quad (1)$$

$$\text{with } \sigma(d) = \sqrt{\frac{2}{\pi}} \bar{V}(d), \quad (2)$$

251 where the mode $\sigma(d)$ is defined such that the mean of the Rayleigh distribu-
 252 tion is equal to the available daily-mean wind-speed $\bar{V}(d)$ at the gridpoint.
 253 The effect of this parameterization of intraday wind fluctuations on the wind
 254 capacity factor of the north region is shown in Figure 3a and 3b, for a sample
 255 week in winter and another in summer 2010, respectively. One can see how
 256 the capacity factor increases with the daily-mean wind-speed, as well as the
 257 variance of intraday fluctuations due to the parameterization. However, it
 258 is clear from the figure that the intraday variability of the capacity factor is
 259 underestimated, a discrepancy that should be improved in future versions of
 260 the model.

⁶ Note that, due to the bias correction (see Sect. 2.2.2), only the variability of the wind production may be sensitive to this choice of power curve.

⁷This correction is applied to the wind speed rather than directly to the wind production in order to shift the power curve horizontally rather than scale it vertically and hence preserve the cut-in and cut-out behavior of the turbine.

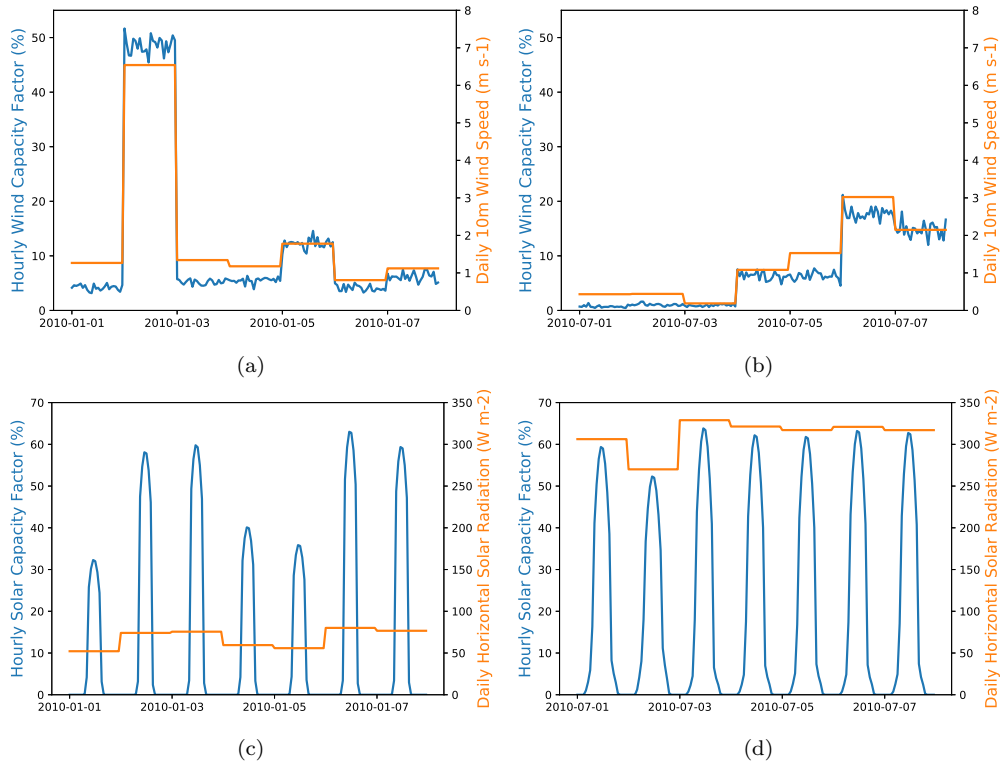


Figure 3: Illustration of the intraday parameterization of the wind (top) and solar (bottom) generation for the north region, the first week of January 2010 (left) and of July 2010 (right). Top panels represents both the computed hourly wind capacity factor (blue) and the daily-mean wind-speed (orange) from which the former is calculated. Bottom panels represents both the computed hourly solar capacity factor (blue) and the daily-mean horizontal surface radiation (orange) from which the former is calculated.

261 We simulate the PV production for arrays at each gridpoint composed
 262 of multi-crystalline silicon solar cells. The crystalline silicon solar cell occu-
 263 pies about 90% of the PV market, among which multi-crystalline solar cells
 264 have the highest share at 53% and mono-crystalline solar cells have a 33%
 265 share (Hosenuzzaman et al., 2015). Each module has a nominal power of
 266 250 Wm^{-2} for an area of 1.675 m^2 , resulting in a reference efficiency of about
 267 15%⁸. The real efficiency of the cell is, however, dependent on its tempera-
 268 ture, which is itself dependent on the air temperature and the wind from the

⁸The nominal power itself is not important here, as only capacity factors are used

269 WRF dataset and on the global tilted irradiance (see below). This depen-
 270 dence is modeled using the thermal model described in Duffie and Beckman
 271 (2013, Chap. 23)⁹. The efficiency of the overall electrical installation behind
 272 the modules is assumed to be of 86%.

273 Solar radiation from WRF is partitioned into direct, diffuse and reflected
 274 components (Duffie and Beckman, 2013, Chap. 2.16) at every gridpoint. This
 275 partitioning depends on the clearness index \bar{K}_T and elevation angle of the
 276 sun at the gridpoint. The quantity $\bar{K}_T(d)$, for some day d , is defined as the
 277 ratio of the horizontal radiation at ground level, $\bar{I}(d)$, to the correspond-
 278 ing radiation available at the top of the atmosphere, i.e. the extraterrestrial
 279 radiation $\bar{I}_0(d)$.

280 In order to take into account the effect of the diurnal cycle on the tilted
 281 irradiance, which accounts for most of the variance of the solar production
 282 (see Sect. SI-1), the hourly extraterrestrial solar radiation, $I_0(d, h)$, is com-
 283 puted for every hour h from the calendar information. The hourly horizontal
 284 radiation at the surface, $I(d, h)$, for the hour h of the day d is then computed
 285 by multiplying the hourly extraterrestrial radiation $I_0(d, h)$ by the clearness
 286 index $\bar{K}_T(d)$, assumed constant throughout the day. In other words,

$$I(d, h) = \bar{K}_T(d) I_0(d, h) \quad (3)$$

$$\text{with } \bar{K}_T(d) = \frac{\bar{I}(d)}{\bar{I}_0(d)}. \quad (4)$$

287 Each array is assumed to be tilted by an angle equal to the latitude of
 288 the array and to face due South. To separate the diffuse component from the
 289 direct component of the global horizontal irradiance, the model from Reindl
 290 et al. (1990a) is used. For solar elevations below 10° and when the sun is
 291 behind the array, the direct horizontal irradiance is set to zero. The diffuse
 292 component of the tilted irradiance is computed following the model of Reindl
 293 et al. (1990b). The reflected component of the tilted irradiance depends on
 294 the zenith angle and follows the usual formula given by Duffie and Beckman
 295 (2013, Chap. 2.16) with an albedo of 0.2^{10} .

⁹ The thermal model is configured for relatively common parameter values for crystalline cells, i.e., for a temperature coefficient of 0.004 K^{-1} , a reference temperature of 25°C and a cell temperature at nominal operating cell temperature of 46°C (Skoplaki and Palyvos, 2009).

¹⁰The global tilted irradiance tends, however, to be dominated by its direct and diffuse

296 The effect of the diurnal cycle on the solar capacity factor of the north
 297 region is shown in Figure 3c and 3d, for a sample week in winter and another
 298 in summer 2010, respectively. One can see how the solar production varies
 299 with the diurnal cycle and how this cycle is modulated by the clearness of
 300 the atmosphere. On the other hand, no variability associated with intraday
 301 changes in, e.g., the cloud cover is present since the clearness index remains
 302 fixed throughout the day. The variance of the solar capacity factor may thus
 303 be underestimated. This discrepancy should, however, remain limited to the
 304 extent that intraday variations of the clearness index are averaged out by the
 305 regional averages.

306 2.2.2. Aggregation and bias correction

307 The regional wind and PV capacity factors are obtained by dividing the
 308 computed production by its nominal value and then aggregating at regional
 309 level on an hourly basis. In so doing, a strong bias (up to 100%) is found
 310 between the yearly-averages of the computed capacity factors and the region's
 311 capacity factors computed from the GSE data (Table 1). Since the second
 312 moment of the capacity factors roughly scales with their mean, we re-scale the
 313 computed capacity factors so that their average over the climate-data period
 (1989–2012) coincide with the GSE averages over the 2013–2017 period.

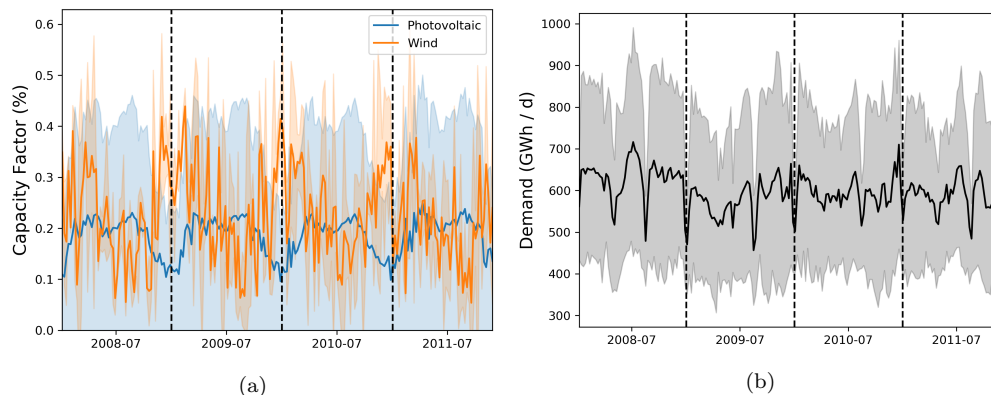


Figure 4: Time evolution of weekly-averaged PV (orange) and wind (blue) capacity factors (a) and demand (b). The shadings represent the standard deviation of the time series.

314

components.

315 Figure 4a represents the weekly and regionally-averaged PV (orange) and
 316 wind (blue) capacity factors for a few sample years. Seasonal cycles of PV
 317 and wind energy production are phase shifted, with wind energy produc-
 318 tion (PV) peak yield in winter (summer). Wind energy production is also
 319 characterized by a stronger sub-seasonal variability when compared to PV at
 320 large-scale. Both the mean and the variance of the capacity factors for the
 321 wind production tend to be larger than those of the photovoltaic production.
 322 Albeit complementary over the year the wind and solar production requires
 323 additional energy inputs from other sources to counterbalance some recurrent
 324 short term deficit between the demand and the wind and solar production.

325 Let us insist that the present bias correction only corrects for differences
 326 in the first moment of the capacity factors with the observed values. For the
 327 analysis of Section 4, higher moments, in particular the variance and covari-
 328 ance, are also important. Although one expects the variance of the capacity
 329 factors to scale with their mean, discrepancies may persist. Our computa-
 330 tions are tested against observations for bias in the variance in the SI-1.

331 Note finally that the conventional production, which includes here ther-
 332 mal as well as hydropower plants, is not explicitly modeled in this study and
 333 is left for future work.

334 2.2.3. Electricity demand model

335 Since we are primarily interested in the impact of climate variability and
 336 change on the demand, the objective of the model is to predict the part of the
 337 daily regional demand depending on climate, in particular on the surface air
 338 temperature¹¹, while preserving the statistics associated with other factors.

339 We follow a statistical learning approach (Hastie et al., 2009) whereby the
 340 model is trained against the regionally-averaged temperature data from the
 341 WRF model as input and the regionally-averaged demand data from GME
 342 as output, from the beginning of 2005 to the end of 2011 (i.e. the intersection
 343 of the climate with the demand record).

344 Let the electricity demand D_{in} for the region i at the time step n and for
 345 a particular type of day (see below) be given by

$$D_{in}(T_i) = f_i(T_{in}) + \epsilon_{in}. \quad (5)$$

¹¹ Other variables, such as the specific humidity, the wind, or the irradiance where not found to significantly affect the demand, in this case.

346 where $f_i, 1 \leq i \leq N$ is some real-valued function of the daily-mean tempera-
 347 ture T_{in} in the region i at the time step n (T_{in} is the same for two hours of
 348 the same day), and the residual ϵ accounts for other factors impacting the de-
 349 mand, such as changes in the population, the economy, tourism, individuals
 350 decisions, etc.

351 It is known that the demand has a nonlinear dependence on the temper-
 352 ature. Electric heating is switched on only for lower temperatures, while air
 353 conditioning is switched on only for higher temperatures. This can be seen
 354 in Figure 4b for Italy. The demand has two main peaks per year, one during
 355 winter and one during summer, and lows in spring and fall and during hol-
 356 idays. In winter, the consumption peak is due to heating, especially in the
 357 northern part of Italy (see below). In summer, the consumption peak is due
 358 to tourism and air conditioning (Terna, 2016). Figure 4 shows that, except
 359 for the summer period, wind energy production is well correlated with the
 360 demand, whereas PV production is negatively correlated with the latter.

361 Once an individual appliance is switched on, its electricity consumption
 362 is to a first approximation linear in the temperature. Assuming, that all
 363 consumers behave in the same way and that a consumer switches the heater
 364 (air conditioning) for a constant temperature threshold T_H (T_C), we define
 365 the functions f_i as a piecewise-linear function of the temperature. In addi-
 366 tion, the behaviour of the consumers differs significantly for the week days,
 367 Saturdays, and Sundays and holidays (respectively marked *work*, *sat* and *off*,
 368 in the following) and the demand is known to strongly depend on the hour
 369 of the day (see SI-1). We thus choose to modulate the daily demand by a
 370 composite cycle which only depends on the hour of the day and the day type.
 371 The resulting model is given by,

$$f_i(T_{in}) = \begin{cases} f_i^{\text{work}}(T_{in}) & \text{if the day at } n \text{ is a working day} \\ f_i^{\text{sat}}(T_{in}) & \text{if the day at } n \text{ is a Saturday} \\ f_i^{\text{off}}(T_{in}) & \text{if the day at } n \text{ is a holiday,} \end{cases} \quad (6)$$

$$\begin{aligned} \text{with } f_i^{\text{work|sat|off}}(T_{in}) &= a_H^{\text{work|sat|off}} \Theta(T_H - T_{in})(T_H - T_{in}) g_n^{\text{work|sat|off}} \\ &+ a_C^{\text{work|sat|off}} \Theta(T_{in} - T_C)(T_{in} - T_C) g_n^{\text{work|sat|off}} \\ &+ a_0^{\text{work|sat|off}} g_n^{\text{work|sat|off}} \end{aligned}$$

372 where Θ is the Heaviside step function¹² and the coefficients $g_n^{\text{work|sat|off}}$ are
 373 given by the average — over all days of the same day type and all hours of
 374 the same hour of the day — of the observed demand on which the model is
 375 trained. The model (6) has a total of 9 parameters $a_H^{\text{work|sat|off}}$, $a_C^{\text{work|sat|off}}$ and
 376 $a_0^{\text{work|sat|off}}$ to be adjusted, for each region.

377 The resulting linear model is fitted assuming that the thresholds T_H and
 378 T_C are constant over all regions and all day types. These thresholds con-
 379 stitute two hyper-parameters that we select via a grid-search with a cross-
 380 validation (Hastie et al., 2009) over seven blocks of one year.

381 The linear model is fitted using the Bayesian ridge regression method
 382 (MacKay, 1992) both to avoid over-fitting and to take into account the vari-
 383 ance arising from factors that are not fully resolved by the deterministic
 384 part of the model¹³. A time series of the hourly regional demand over 1989–
 385 2012 is predicted from the full length of the temperature record by randomly
 386 drawing samples from the posterior distribution of the model at each time
 387 step. The way the Bayesian model operates is illustrated in Figure 5 where
 388 the predicted demand for the north region the first week of January 2010 is
 389 shown (plain blue line) together with the input daily-mean temperature T_{in}
 390 (plain orange line) and the series of composite daily cycles $g_n^{\text{work|sat|off}}$ (dashed
 391 blue line).

392 The resulting prediction of the regional demand is represented (only for
 393 daily-means) in Figure 6 versus the input temperature. The overall coeffi-
 394 cient of determination is 0.73. One can see that the temperature and type
 395 of day dependence of the demand is most clear for the economically most
 396 dynamic north region. This is also true, yet to a lesser extent, for the central
 397 south region. The shaded regions show that the part of the demand that
 398 is not explained by the temperature model is compensated by the Bayesian
 399 perturbations, although in a random fashion.

400 To conclude, this method, as apposed to using the 13 years of observed
 401 demand provided by GME, allows to estimate the demand over the longer

¹² The relationship between the demand and the ambient temperature in European countries is smoother than a piecewise-linear function (Bessec and Fouquau, 2008), in part due to the non-homogeneous behaviour of the consumers. Here, however, we prefer to keep the model as simple as possible using the above linear basis.

¹³ The implementation from *scikit-learn* (Buitinck et al., 2013) of the Bayesian ridge regression is used, whereby the residual and the weights are given zero-mean isotropic Gaussian priors. The variances of the latter are given as priors gamma distributions.

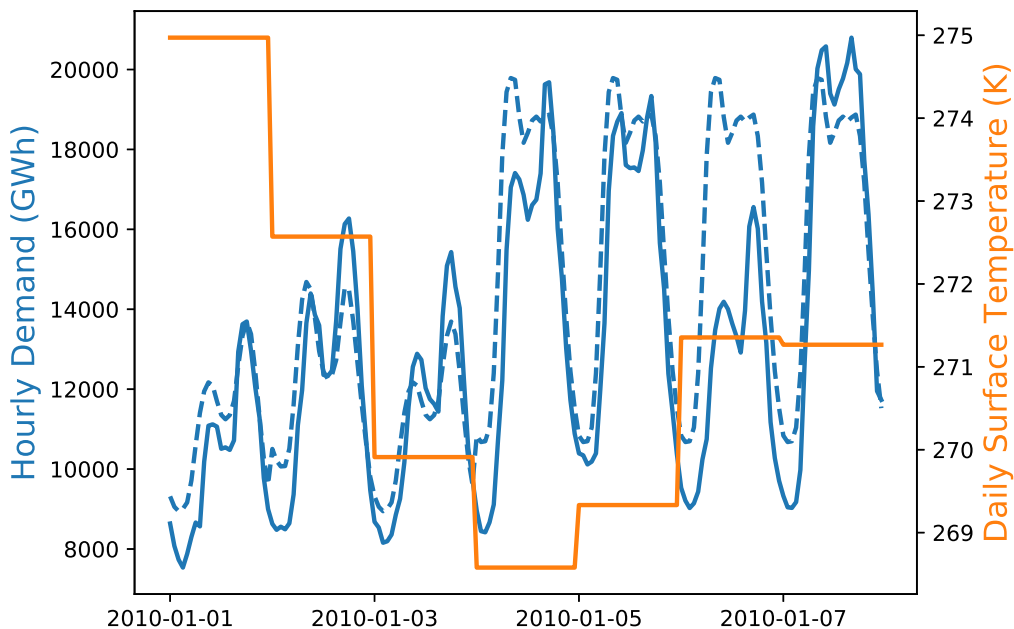


Figure 5: Illustration of the intraday parameterization of the demand for the north region the first week of January 2010. The computed hourly demand (plain blue line) is obtained by modulating the series of composite daily cycles $g_n^{\text{work|sat|off}}$ for each day type (dashed blue line) by the function (6) of the daily-mean temperature (plain orange line) and by adding random perturbations drawn from a normal distribution whose variance depends both on the noise in the demand and the uncertainty in the parameters of the model.

402 record of the climate data so as to take into account variations in the demand
 403 due to low-frequency temperature variability¹⁴.

404 3. Mean-variance analysis

405 Geographic and technological diversification of renewable power plants is
 406 based on a mean-variance analysis that is inspired by Markowitz's modern
 407 portfolio theory¹⁵.

¹⁴Note that, assuming that the demand-temperature relation in (6) is valid, low-frequency climate variability may be responsible in changes in the coefficients of the model over periods longer than the observed demand record over which the model is fitted.

¹⁵ See, for example, Mencarelli and D'Ambrosio (2018) for a survey on mathematical programming approaches for the portfolio selection problem.

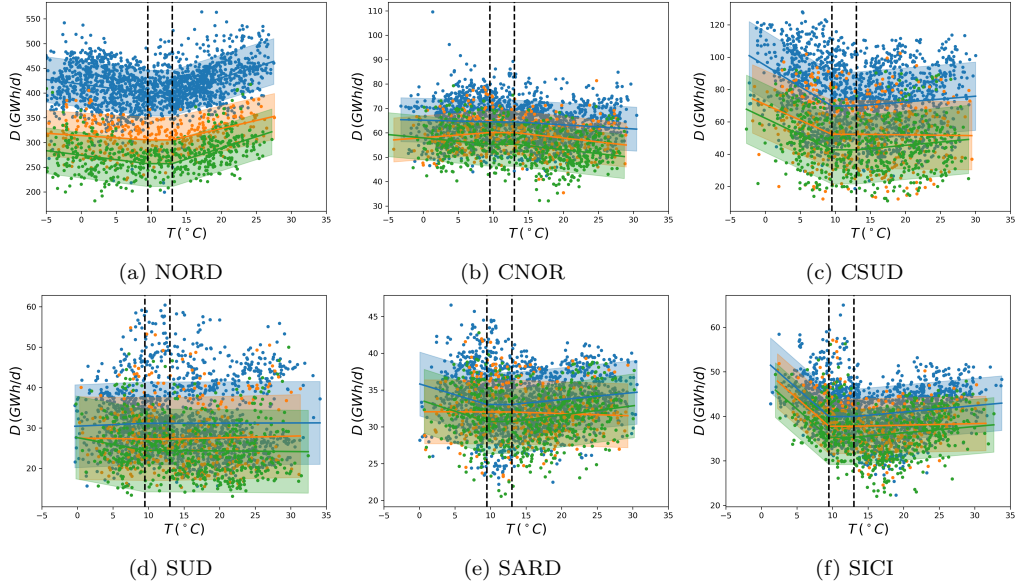


Figure 6: Daily-mean electricity demand for each zone versus the surface temperature. Each point is an observed realization of temperature and demand. The lines represent the functions $f_i^{\text{work|sat|off}}$ of the demand model, while the associated shaded regions represent the variance of the prediction. Blue, orange and green data points and functions correspond to working days, Saturdays, and Sundays and holidays, respectively. The two vertical dashed lines represent the temperature thresholds $T_H = 9.5$ and $T_C = 13.0$.

408 In our context, the mean-variance analysis refers to the process of find-
 409 ing optimal spatial and technological distributions of renewable energy pro-
 410 duction achieving a trade-off between the mean penetration rate and some
 411 measure of the variance in the renewable energy production. The variance
 412 is a proxy for the risk: minimizing the variance corresponds to maximizing
 413 the diversification of the renewable configuration, which in turn lowers the
 414 variability of renewable energy penetration and improves the flexibility of
 415 the system and its resistance to shocks. In particular, a lower variance in
 416 the renewable energy mix is less demanding in services from conventional
 417 production (for which start up and shutting down services have a cost) or
 418 demand management.

419 Each renewable mix may then be represented in a mean-variance chart.
 420 As a bi-objective optimization problem (Miettinen, 1999), mixes are to be
 421 optimal in the Pareto sense. A solution is said to be Pareto optimal if there
 422 exists no feasible solution with a better or equal value for each of the objective

423 functions (with at least one of these values being strictly better).

424 Let us consider as an example Figure 7. The points under or to the right
 425 of the frontier are by definition suboptimal and will be discarded by a rational
 426 investor. The area above or to the left of the frontier cannot be reached.

427 Two variations of the mean-variance analysis are considered here. In
 428 both, the mean RES penetration μ is given by the fraction of the expected
 429 total production over the expected total demand¹⁶, i.e.

$$\mu := \frac{\mathbb{E} [\sum_{\mathbf{k}} w_{\mathbf{k}} \eta_{\mathbf{k}}]}{\mathbb{E} [\sum_i D_i]} = \frac{\sum_{\mathbf{k}} w_{\mathbf{k}} \mathbb{E} [\eta_{\mathbf{k}}]}{\mathbb{E} [\sum_i D_i]}, \quad (7)$$

430 where $\mathbf{k} = (i, j)$ is the multi-index composed of a regional index i in {NORD,
 431 CNOR, CSUD, SUD, SARD, SICI} and a technological index j in {PV, wind},
 432 the $w_{\mathbf{k}}$ are the installed capacities for each region and technology, the $\eta_{\mathbf{k}}$ are
 433 the corresponding predicted time-dependent capacity factors (Sect. 2.2.1)
 434 and the D_i are the predicted regional demands (Sect. 2.2.3). Note that, in
 435 the following numerical applications, statistics such as the expectation or
 436 the covariance are replaced by sample estimates from the full records (1989–
 437 2012).

438 In the first strategy, also called *global*, it is assumed that each region
 439 produces electricity to satisfy the total demand in priority with no consider-
 440 ation for their local demand or for transmission constraints between regions.
 441 In other words, the electricity produced at a given location is immediately
 442 available to meet the overall Italian demand. In this case, the risk squared
 443 $\sigma_{\text{global}}^2(\mathbf{w})$ is defined as the variance of the sum of the regional RES produc-
 444 tions normalized by the total demand, i.e.

$$\sigma_{\text{global}}^2(\mathbf{w}) := \mathbb{V} \left[\frac{\sum_{\mathbf{k}} w_{\mathbf{k}} \eta_{\mathbf{k}}}{\sum_i D_i} \right] = \sum_{\mathbf{k}} \sum_{\mathbf{l}} w_{\mathbf{k}} G_{\mathbf{k},\mathbf{l}}^{\text{global}} w_{\mathbf{l}}, \quad (8)$$

445 where $G_{\mathbf{k},\mathbf{l}}^{\text{global}} := \text{Cov}[\eta_{\mathbf{k}}/\sum_i D_i, \eta_{\mathbf{l}}/\sum_i D_i]$ is the covariance matrix between
 446 the capacity factors normalized by the total demand for each pair of regions
 447 and technologies.

¹⁶The normalization by the mean total demand in the definition (7) of the mean pene-
 tration has no effect on the relative distribution of the capacities in the optimal problem.

448 In the second strategy, also called *regional*, each region attempts to satisfy
 449 its local demand in priority. If the electrical production is larger than the
 450 demand, electricity can be exported. The risk squared $\sigma_{\text{regional}}^2(\mathbf{w})$ is thus
 451 defined as the sum of the variances of the regional production normalized by
 452 the regional demand.

$$\begin{aligned} \sigma_{\text{regional}}^2(\mathbf{w}) &:= \sum_i \mathbb{V} \left[\frac{w_{(i,\text{PV})}\eta_{(i,\text{PV})} + w_{(i,\text{wind})}\eta_{(i,\text{wind})}}{ND_i} \right] & (9) \\ &= \sum_{\mathbf{k}} \sum_{\mathbf{l}} w_{\mathbf{k}} G_{\mathbf{k},\mathbf{l}}^{\text{regional}} w_{\mathbf{l}}, \end{aligned}$$

453 where $G_{\mathbf{k},\mathbf{l}}^{\text{regional}} := \text{Cov}[\eta_{\mathbf{k}}/(ND_i), \eta_{\mathbf{l}}/(ND_j)]$ if $i = j$, 0 otherwise¹⁷.

454 Note that in the global and the regional definitions of the risk, the RES
 455 production is normalized by the total and by the regional demand, respec-
 456 tively. This is particularly important for the regional optimization as nor-
 457 malizing by the local demand favors installing RES capacity in proportion
 458 to the latter.

459 The goal of this study being to assess the optimal recommissioning of the
 460 Italian renewable energy mix, we also consider constraining the total installed
 461 RES capacity to its observed value $w_{\text{total}} = 27.7$ GW in 2015 (Sect. 2.1). The
 462 mean-variance analysis, thus, consists in solving, the optimization problem

$\min_{\mathbf{w}}$	$\sigma_{\text{global regional}}^2(\mathbf{w})$	(10a)
$\max_{\mathbf{w}}$	$\sum_{\mathbf{k}} w_{\mathbf{k}} \mathbb{E}[\eta_{\mathbf{k}}]$	(10b)
subject to	$\sum_{\mathbf{k}} w_{\mathbf{k}} = w_{\text{total}}$	(10c)
	$w_{\mathbf{k}} \geq 0 \quad \forall \mathbf{k}.$	(10d)

463 Assuming that the share of the demand that is not satisfied by RES is sup-
 464 plied by the conventional production normalized by the demand, the opti-
 465 mization problem (10) is equivalent to minimizing both the mean and the
 466 variance of the conventional production. Taking into account the full power

¹⁷ The division by the number of regions N in (9) is there for comparison with the global risk (8).

467 flow of the transmission network together with the conventional production
 468 is left for future work.

469 The classical method used in the following Section 4 to approximate the
 470 optimal frontier numerically is explained in SI-2. In this study, we refer to
 471 the optimal frontier as the curve $(\sigma_{\text{global|regional}}(\hat{\mathbf{w}}), \mu_{\text{global|regional}}(\hat{\mathbf{w}}))$, where
 472 the $\hat{\mathbf{w}}$ are the optimal solutions, although, strictly speaking, it is the risk
 473 squared that is minimized rather than the risk itself. The numerical results
 474 of the following section suggest that the so-defined frontier of the bi-objective
 475 problem (10) without the total capacity constraint (10c) is a half line with a
 476 positive slope that we refer to as the *mean-risk ratio* $\alpha_{\text{global|regional}}$. In other
 477 words, the optimal mixes for this problem are such that

$$\mu_{\text{global|regional}}(\hat{\mathbf{w}}) = \alpha_{\text{global|regional}} \sigma_{\text{global|regional}}(\hat{\mathbf{w}}), \quad (11)$$

478 In the following, we assume that this is indeed the case and the mean-risk ra-
 479 tio $\alpha_{\text{global|regional}}$ is used to diagnose the variants of the optimization problem.
 480 The proof of a rigorous mathematical result is left for future work.

481 4. Optimizing the distribution of wind and solar generation

482 *Global* and *regional* strategies are represented in Figure 8 (upper and
 483 lower panels respectively). Each point of the frontier represents an optimal
 484 combination of the capacities that maximizes the penetration for a given risk,
 485 while satisfying the constraints. The mixes in the region below or to the right
 486 of the efficient frontier are suboptimal. The straight black line represents an
 487 approximation of the optimal frontier of the same problem, but with the total
 488 capacity constraint (10c) removed.

489 One may first observe that the optimal frontiers of the *regional* strategy
 490 (Fig. 8c) are shifted towards lower risk values compared to the frontiers of
 491 the *global* strategy (Fig. 8a). This shift is due to the different definitions (8)
 492 and (9) of the risk for the two strategies, respectively. It does not provide
 493 an objective argument to choose a regional policy over a global one. Instead,
 494 a trade-off exists between a strategy in which all regions cooperate for the
 495 national welfare and a strategy in which each region attempts to meet its
 496 own demand in priority¹⁸.

¹⁸ Recall from Sect. 3, that in this study, the constraints imposed by the conventional production and transmission network capacities are not considered.

497 The mean-risk ratio $\alpha_{\text{global|regional}}$ (the slope of the black curves) of the
498 optimization problems without the total capacity constraint is also given
499 in the sub-captions. It is of 1.69 for the *global* strategy and of 3.71 for
500 the *regional* strategy. Increasing the mean penetration of the optimal mix
501 necessarily comes at the price of an increased risk. For the same level of total
502 mean penetration, adding the constraint on the present total capacity (blue
503 curve) necessarily deteriorates the risk.

504 The point at which both frontiers join (in black) corresponds to the opti-
505 mal mix for which the total capacity constraint is inactive. This means that,
506 for this level of mean penetration, the mix minimizing the risk naturally sat-
507 isfies the total capacity constraint. It is thus the optimal mix satisfying the
508 total capacity constraint that has the maximum mean-risk ratio. If no pref-
509 erence is put on maximizing the mean penetration or minimizing the risk,
510 this optimal mix is attractive. In the following, we refer to this mix as the
511 *maximum mean-risk ratio scenario*.

512 Yet, one may be interested in allowing for the deterioration of the mean-
513 risk ratio in order to either decrease the risk or increase the total penetration.
514 The blue dots in Fig. 8a and 8c correspond to the optimal mixes minimizing
515 the risk. Their mean-risk ratio is then lowered to a value of 1.61 for the
516 global strategy and of 3.53 for the regional strategy. We refer to this mix
517 as the *minimum risk scenario*. For comparison with the actual mix the blue
518 diamond in Fig. 8a and 8c represents the optimal mix that satisfies the same
519 level of risk as the actual mix (gray dot) while maximizing the penetration
520 rate. We refer to this mix as the *high penetration scenario*.

521 Some important properties of the optimal mixes with the constraint on
522 the total capacity are represented on the right panels of Fig. 8. The PV ratio,
523 i.e. the fraction of photovoltaic capacity in the mix, is plotted in orange. A
524 value of 100% (0%) corresponds to 100% (0%) PV production 0% (100%)
525 wind energy production. The plain and dashed green curves represent the
526 frequency of occurrence of shortage and saturation, respectively. Shortage
527 situations are associated with insufficient energy production. This situation
528 corresponds to large scale blocking atmospheric patterns associated with cold
529 or heat waves and low renewable energy production, especially from wind.
530 These configurations lead to underproduction of electricity from PV and
531 wind farms. Here, it is assumed that conventional generation units are able
532 to meet up to 80% of the maximum demand modeled. Shortage then occurs
533 if the photovoltaic and wind generation is not able to meet the rest of the
534 demand. In this case, electricity needs to be imported from the neighboring

535 countries (which is not explicitly accounted for in our modeling framework).
536 Moreover, shortage situations result in an increase in the electricity market
537 price and add pressure on power networks at continental scale. The second
538 critical situation corresponds to network saturation, when electricity produc-
539 tion from wind and PV plants is too large for the network and exceeds the
540 technical limit of renewable energy fraction in the energy mix. In this study,
541 saturation is defined to occur if more than 40% of the demand is met by pho-
542 tovoltaic and wind sources. High probability of occurrence of such situations
543 may jeopardize the funding system for renewable energy infrastructures and
544 may lead to network instability. It can also generate very low or even neg-
545 ative electricity prices (in Italy the prices cannot be negative, the floor is 0
546 euro), jeopardizing the profitability of the conventional power plants, which
547 are essential for network security. Figures 8d and 8d show the fraction of
548 installed PV capacity and the frequency of occurrence of shortage and satu-
549 ration situations as a function of the mean penetration for the global and
550 the regional strategy, respectively.

551 One can first see that the PV ratio is a decreasing function of the mean
552 penetration reached by the mix. This is explained by the fact that the
553 capacity factors from the wind generation are higher than those from the
554 photovoltaic generation (cf. Tab. 1). Moreover, the shortage and the satu-
555 ration curves (in green) have a distinct global minimum. The convexity of
556 both curves is due to the fact that the probability of occurrence of extremes
557 increases with the risk and that the latter increases faster for both smaller
558 and larger values of the mean penetration. The vertical lines in Fig. 8b
559 and 8d represent the level of mean penetration for the minimum risk, max-
560 imum mean-risk ratio and high penetration scenarios. The minimum risk,
561 the maximum mean-risk ratio and the high penetration scenarios respectively
562 include 45%, 33% and 19% of PV capacity in the mix. The minimum risk
563 scenario is relatively close to the minimum of saturation occurrence, while
564 the maximum mean-risk ratio and the higher penetration scenarios are close
565 to the minimum of shortage occurrence. Thus, favoring the minimization
566 of the risk also allows to avoid saturation situations, while increasing the
567 mean penetration allows to avoid shortage situations. Overall, the regional
568 problem suggests installing more photovoltaic capacity than wind capacity
569 compared to the global problem.

570 We represent in Figure 9 the resulting spatial distributions correspond-
571 ing to the three scenarios for both the global and the regional problems.
572 Focusing on the global problem, the minimum risk scenario distributes all

573 the PV capacity in the north region, while achieving higher levels of mean
574 penetration requires to move the PV capacity to the south and to Sicily. For
575 all scenarios, the wind capacity is relatively spread over all regions but the
576 central south one.

577 The resulting capacity distribution for the regional strategy (right panels
578 of Fig. 9) is dramatically different from that for the global strategy. In-
579 deed, most of the RES capacity is installed in the north region, whatever the
580 scenario, with more wind capacity to increase the mean penetration. Only
581 minimal capacity is installed in the central north, Sardinia and Sicily. This
582 can be understood from both facts that the definition of the risk for the
583 regional problem favors minimizing the risk of each region individually be-
584 fore minimizing the total risk and that the capacity factors in the risk are
585 normalized by the demand. Since most of the demand occurs in the north
586 (cf. Table 1), the variance of the capacity factors in that region is given less
587 weight than the others in the definition of the regional risk. This corresponds
588 to an incentive for the north region to satisfy its demand with its own RES
589 resource first.

590 The results obtained so far show a strong dependence of the optimal mix
591 on the level of risk that should be achieved. A mix favoring a high level of
592 mean production at the expense of the risk — like in the high penetration
593 scenario — yields a very different PV ratio and geographical distribution of
594 the renewable capacity than in mixes favoring a lower level of risk — like in
595 the the maximum mean-risk ratio and minimum risk scenarios.

596 **5. Discussion**

597 The methodology developed in this article has specifically been designed
598 (i) to exploit correlations between the RES production and the demand and
599 between regions to optimize the renewable energy mix and (ii) to take into
600 account the impact of the climate variability on this mix. This allows us to
601 discuss in this section the role played by climate variability and the potential
602 for improvement of the actual Italian mix.

603 *5.1. Impact of climate variability on the mix*

604 To assess the impact of interannual climate variability (as found in the
605 CORDEX data) on the mix, we repeat the mean-variance analysis succes-
606 sively using data blocks of one year, from 1989 to 2010. In other words, the
607 mix of the 22 mixes that we obtain is optimized for the climatic conditions of

608 a given year. As a result, the optimal mix for one year may be different from
609 the optimal mix for another year due to low-frequency climate variability.

610 We focus on the mixes maximizing the mean-risk ratio α_{global} for the
611 global strategy. From the 22 values of the mean-risk ratios associated with
612 each year, we obtain an estimation of their mean value and of an interval
613 containing 95% of their realizations (see SI-1 for more explanations). The
614 mean-risk ratio α_{global} averages to 1.71 and 95% of its distribution belongs to
615 the centered interval [1.57, 1.85]. Thus, even though the average of the yearly
616 mean-risk ratio is close to the one of 1.69 obtained in Section 4 using the full
617 record, interannual climate variability in the CORDEX data is responsible
618 for year-to-year variations of the mean-risk ratio of up to 8.2%.

619 To go further, we represent in Figure 10 the geographical and techno-
620 logical distribution of the mixes for the year 1989, with a particularly low
621 mean-risk ratio of 1.60, and for the year 1996, with a particularly high mean-
622 risk ratio of 1.85. Due to the steeper optimal frontier for 1996, the mix for
623 the maximum mean-risk ratio scenario achieves both a higher mean total
624 penetration and a lower risk than that for 1989. The distribution of the RES
625 capacity for 1996 also differs from that for 1989 as more wind capacity is
626 installed in the central south and Sardinia regions.

627 It is thus clear that the low-frequency climate variability has a large
628 impact on the optimal mix and that the latter should be taken into account
629 in order to assess future optimal RES mixes that are robust to changes in
630 the climate.

631 *5.2. Comparison with the 2015 Italian mix*

632 The 2015 (actual) Italian mix is composed of 68% PV and 32% wind
633 energy capacity (see Table 2). As can be seen from Figure 2, the largest
634 fraction of installed PV capacity is in the North of Italy, whereas most of
635 wind capacity is located in the South. Indeed, Italy has started investing in
636 renewable energy resources since 1991 (with the feed in tariff CIP6), with
637 the objective of developing national energy sources and so decreasing the
638 dependency on imported gas. Historically, the bulk of PV has been developed
639 in Northern Italy, where the entrepreneurial background has favored local
640 business exploiting renewable energy resources subsidies. Wind farms have
641 been installed in Sicily and Sardinia, where regional specific incentives have
642 been set. Southern Italy has invested in renewable energy more recently,
643 after the reinforcement of the main North-South transmission line.

644 To compare the actual mix with the optimization results, the actual mean
645 penetration and risk are computed for the actual capacity distribution using
646 the same capacity factor and demand data as used to obtain the optimal
647 frontiers of Fig. 8. The corresponding mix is represented by the gray dot
648 in the same figure. This point is not visible in Fig. 8c, for the regional
649 problem, because the value of its risk is several orders of magnitude larger
650 than the x-axis limits. For both the global and the regional problem, the
651 gray point is to the right of the optimal frontiers. The actual mix installed
652 in Italy is thus sub-optimal. For the global problem, this mix reaches a level
653 of mean penetration comparable to that of the minimum risk scenario, but
654 its risk is about 29% larger than that of the latter and its PV ratio about
655 49% higher. The capacity distribution of the optimal mixes in Figure 9
656 may also be compared to that of the 2015 Italian mix in Figure 2. The
657 actual mix appears to be closest to the minimum risk and maximum mean-
658 risk ratio scenarios of the global problem (Fig. 9a). However, the actual
659 mix favors photovoltaic over wind capacities, especially in the north, and
660 that more RES capacity is installed in the central south region. This is
661 in strong contrast with all optimal scenarios. For instance, the maximum
662 mean-risk ratio scenario yields about two third (one third) of wind (solar)
663 capacity. However, these differences may partly be attributable to biases in
664 the intraday variance, as the model tends to underestimate intraday variance
665 of the wind capacity factors and to overestimate the intraday variance of the
666 solar capacity factors (see Table 1)¹⁹.

667 6. Conclusion

668 This work is aimed at developing a proof-of-concept of an integrated
669 modelling framework dedicated to the elaboration of optimal scenarios of
670 renewable energy mix. The proposed framework relies on regional climate
671 simulations. It is shown to be of practical interest for both short and long
672 term renewable energy management, as the model is able to take into account
673 variability in the renewable production and electricity demand from hourly
674 to interannual time scales. The model allows to derive different scenarios
675 consisting in either maximizing the total renewable energy penetration or

¹⁹ Improving the resolution of the intraday variability of the production in the model may require to develop a better parameterization or to rely on additional data. This is left for future work.

676 minimizing the total risk by taking advantage of (anti-)correlations between
677 regions and technologies in an optimal way. Different optimization strategies
678 have been chosen to establish the renewable energy mixes: the first optimiza-
679 tion strategy, the global one, maximizes the national Italian welfare by taking
680 full advantage of correlations between region and by ignoring any potential
681 network constraint; the second strategy, the regional one, assumes that each
682 region maximizes its own welfare in priority, disregarding the potential ben-
683 efit of exploiting cross-regional correlations to improve the national welfare.

684 The main results have been obtained by relying on the full length of
685 the climate record (23 years), in order resolve the impact of interannual
686 climate variability on the optimal mixes as well as possible. By computing
687 additional mixes using only one year of climate data for all available years
688 and by assessing the differences between these mixes, we could show that the
689 impact of interannual climate variability on the optimal renewable energy
690 mix should not be neglected.

691 Comparison with the actual Italian renewable energy mix shows that the
692 actual mix is closer to the global strategy than to the regional strategy as
693 the renewable capacity is relatively evenly spread among regions. However,
694 the scenario maximizing the ratio of the total mean penetration over the risk
695 yields about two thirds (one third) of wind (solar) capacity, in strong contrast
696 with the actual mix containing one third of installed wind capacity. The
697 reasons for such differences are difficult to identify as the actual renewable
698 energy capacity deployment did not follow an optimization elaborated at
699 country scale, but relied on regional policies. Conversely, our optimal energy
700 mix scenarios rely on selected optimization strategies and may be prone to
701 biases in the resolution of the intraday variance of the production.

702 The current framework takes the variance, or risk, of the fraction of the
703 demand covered by the renewable production as a proxy for the flexibility
704 service needed from the hydro and conventional production. Our modeling
705 framework would benefit from the translation of this risk into an economic or
706 a climate cost. For that purpose, the hydro and the conventional production
707 would have to be modeled, taking into account reserve constraints and pri-
708 ority orders between these energy sources. The transmission network would
709 also have to be modeled to take network constraints into account as well as
710 the arbitrage between producing locally and importing/exporting between
711 regions.

712 The current framework is also adapted to consider optimal strategies in
713 a warming climate using 21st century projections from general circulation

714 models. Finally, the generalization of such integrated modeling tool at Euro-
715 Mediterranean scale is a priority. Our framework opens the way for the study
716 of energy transition scenarios at the European scale based on precise mod-
717 eling of climate variability and climate change. The interconnected regions
718 will then be replaced with interconnected countries.

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729 mentation of the model is available at [https://www.lmd.polytechnique.
730 fr/~atantet/TRENDX/](https://www.lmd.polytechnique.fr/~atantet/TRENDX/). It includes a reference guide and a tutorial, allowing
731 one to easily reproduce the results of this study.

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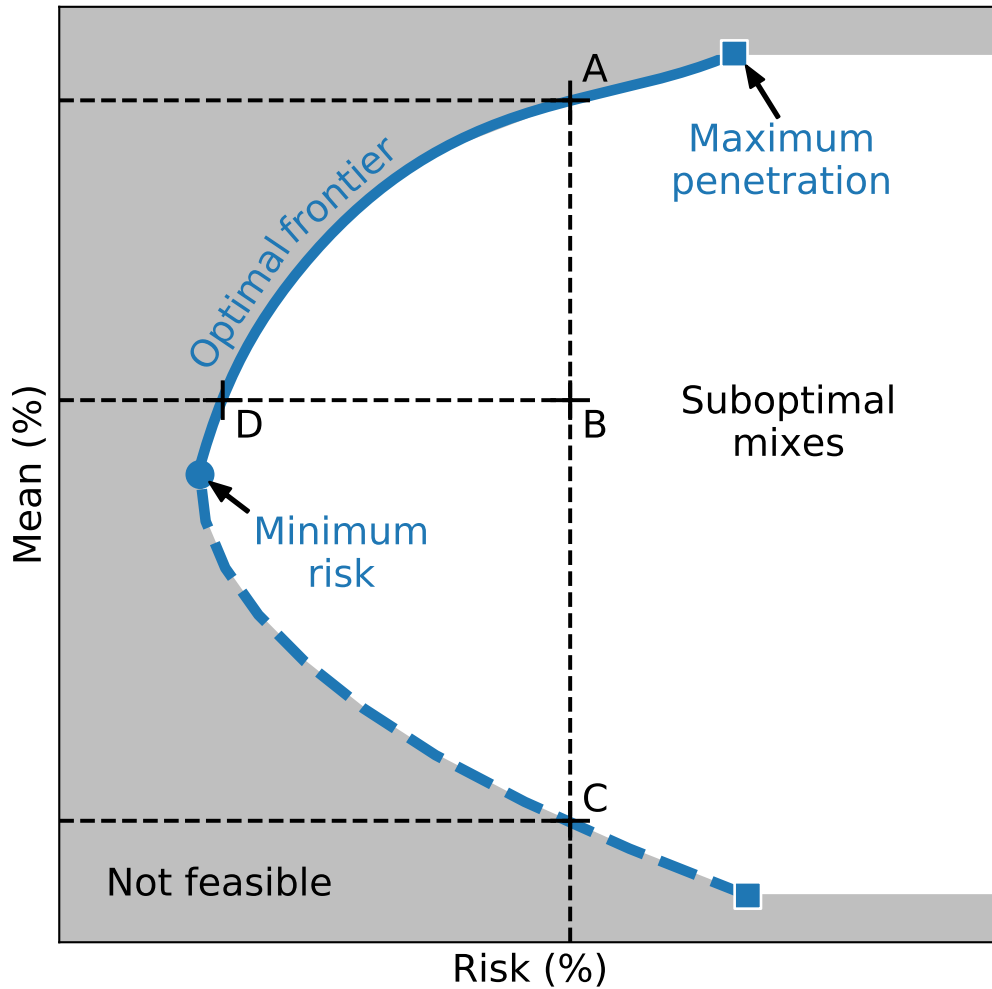


Figure 7: Example of the optimal frontier of a mean-variance bi-objective optimization problem. The optimal frontier is one-dimensional and represented by a plain blue line. Mixes in the white region to the right of the frontier are suboptimal. Points in the gray region to the left of the frontier are not feasible. In this example, the optimal frontier is bounded below by a minimum-risk optimal-mix (blue dot) below which the risk may only increase. The optimal frontier is bounded above by a maximum-penetration optimal-mix above which higher penetration mixes are not feasible due to the constraints of the problem. The point B is an example of suboptimal mix, since a higher mean penetration is achievable for the same risk (point A) and a lower risk is achievable for the same mean penetration (point D). The dashed blue line is obtained by minimizing the risk for a range of target mean penetration values. These solutions are, however, not Pareto optimal. For instance, point C yields the same risk as point A but achieves a lower mean penetration. Thus, A “dominates” C.

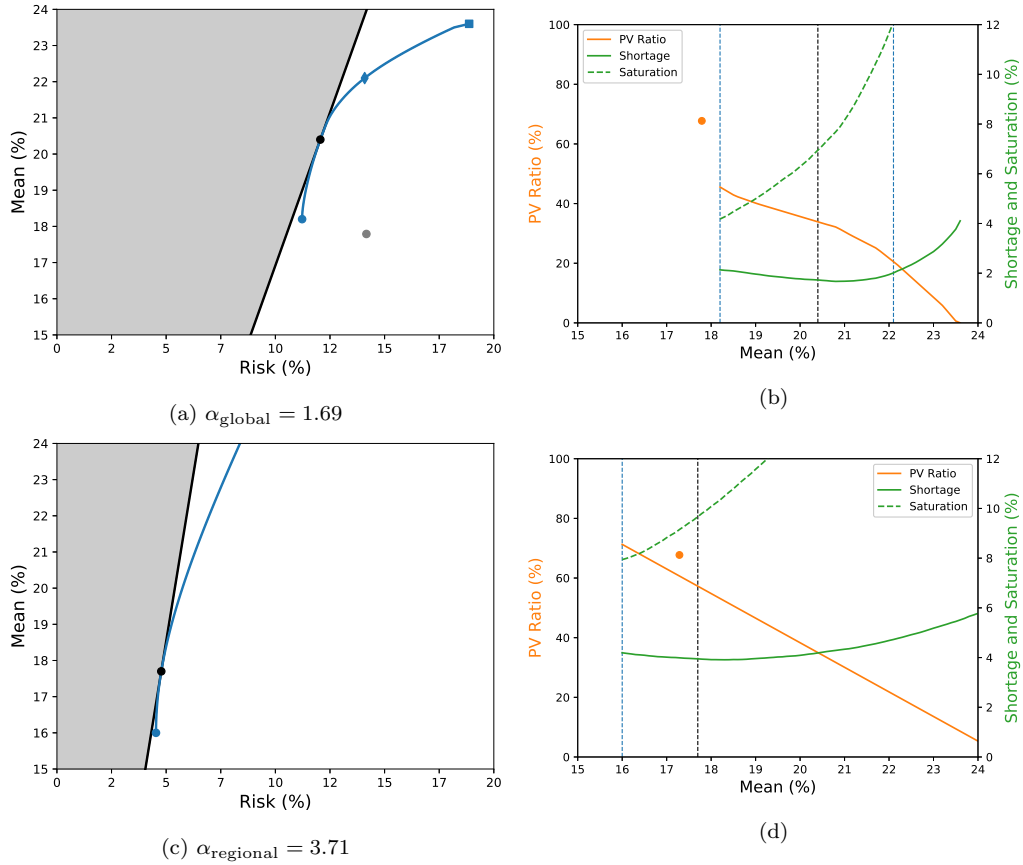


Figure 8: Approximations of the optimal frontiers (left) and of the corresponding electricity mix characteristics (right) for the global (top) and the regional (bottom) optimization problems. The blue curve in the left panels represents the approximation of the optimal frontier of the optimization problem (10). The straight black line is the optimal frontier of the same problem, but with the total capacity constraint (10c) removed. The approximations were obtained using a discretization step of 0.1%. The black dot where the black frontier is tangent to the blue one corresponds to the optimal electricity mix for which the total capacity constraint is inactive (i.e. where adding this constraint has no effect on the results of the optimization problem). The blue dots in panels (a) and (c) correspond to the optimal energy mix for which the risk is minimized while satisfying the total capacity constraint. The gray dot in panel (a) is obtained from the same capacity factor and demand data but applying the actual capacities installed in Italy in 2015 (cf. Tab. 2). The blue diamond corresponds to the optimal mix achieving the same level of risk as the actual mix in gray while maximizing the mean penetration. The blue squares correspond to limits beyond which it is not possible to further decrease or increase the mean total penetration while satisfying the total capacity constraint and the bounds. The values of the mean-risk ratio of the unconstrained optimal frontiers, given by (11), are also reported in the sub-captions. On the right panels are represented the fraction of photovoltaic capacity in the mix (plain orange line), or PV ratio as well as the shortage (plain green line) and saturation (dashed green line) frequencies versus the mean penetration. The blue and black dashed vertical lines mark the mean penetration values corresponding to the blue and black dots and the blue diamond on the left panels. The orange dot represents the PV ratio for the actual capacities installed in Italy in 2015.

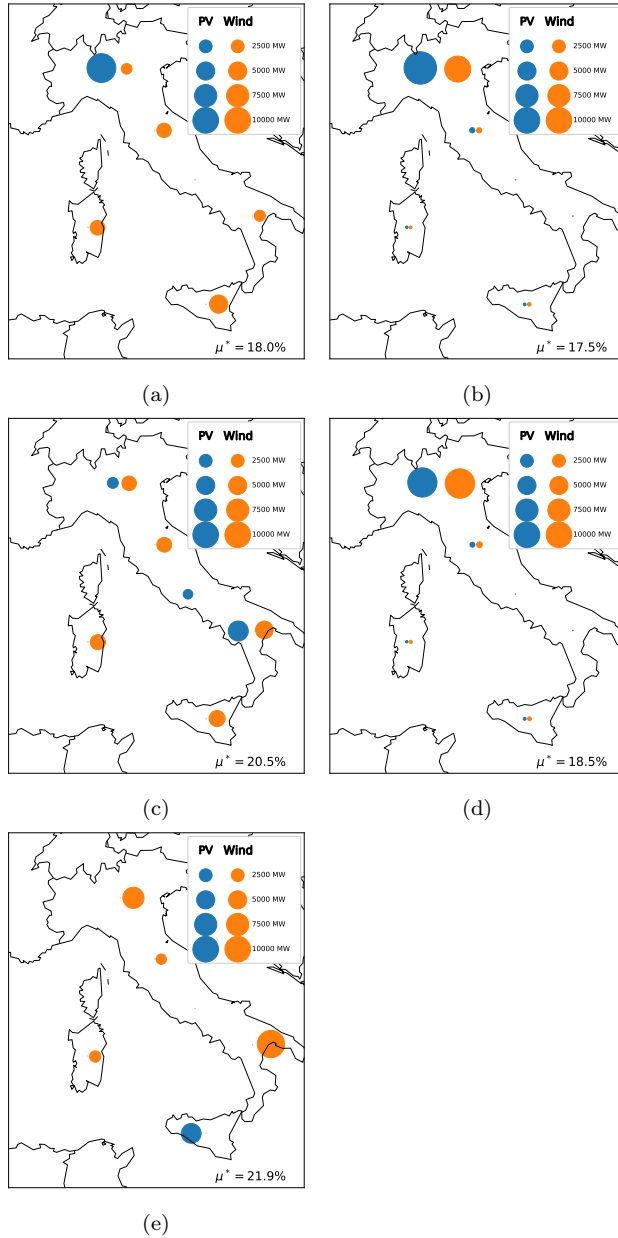


Figure 9: Geographical and technological distribution of the RES capacity for the global (left) and regional (right) optimal mixes respecting the total capacity constraint. The top, middle and bottom panels represent the optimal mixes for the minimum risk, maximum mean-risk ratio and higher penetration scenarios, respectively (blue dot, black dot and blue diamond in Fig. 8a and 8c). Note that there is no plot of the higher penetration scenario for the regional strategy since the regional risk of the actual mix is too high to be achieved by an optimal mix.

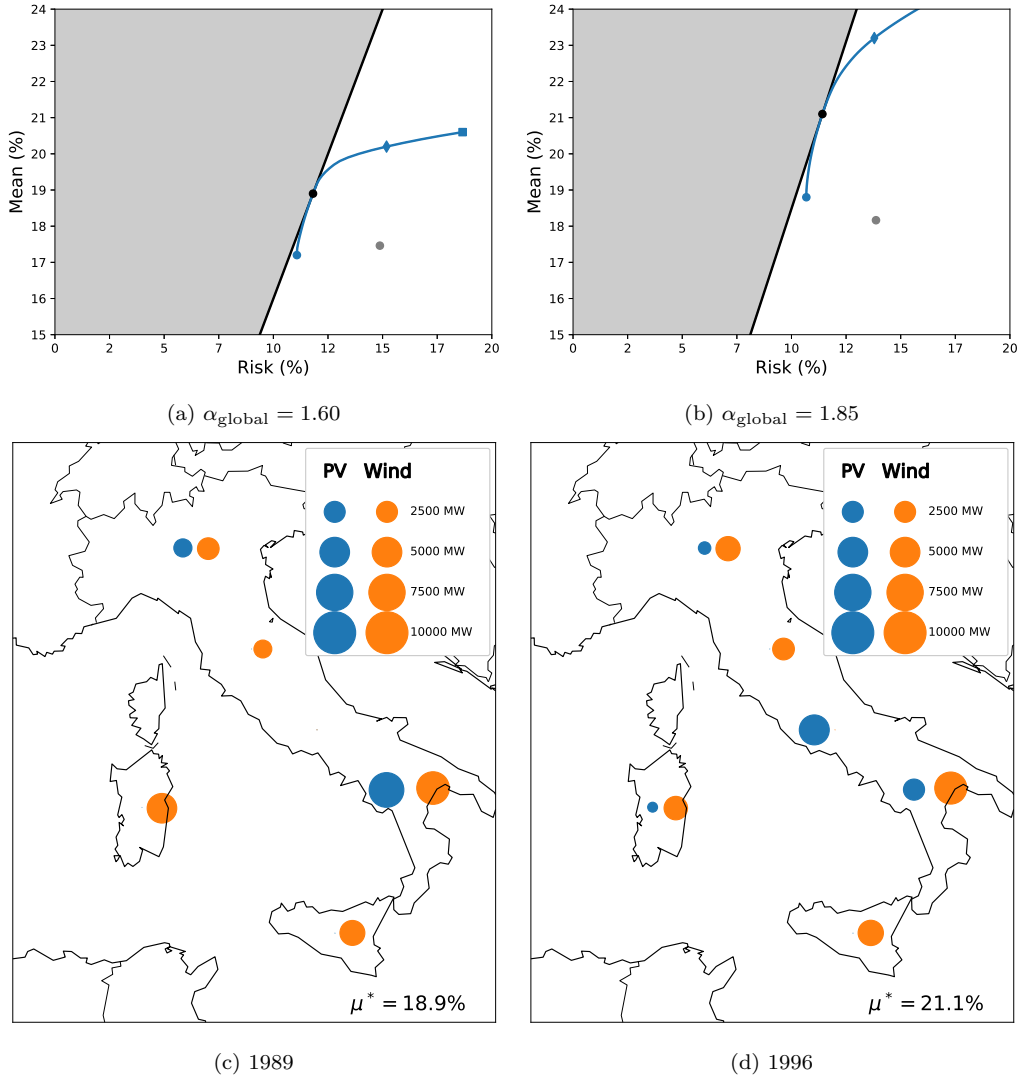


Figure 10: Approximated Pareto frontiers (top) and geographical and technological distribution of the RES capacity (bottom) for the global optimization problem solved for the years 1989 (left) and 1996 (right). The approximations were obtained using a discretization step of 0.1%. The legend is the same as for Fig. 8 and Fig. 9.