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Abstract

Increasing the exploitation of renewable energy sources (RES) is a key element for reducing the detrimental consequences of greenhouse gases emissions and for satisfying the growing demand for energy once fossil fuels will be depleted. Among RES, solar power plays a central role having the potential, by itself, to completely satisfy the world energetic needs. Locating optimal sites where to install solar plants becomes then an important task since this choice can affect the long term profitability of such plants.

The present paper proposes a filtering method to select a subset of efficient locations in order to reduce the dimensionality of the original problem when a large territory is screened in order to locate optimal sites for large-scale solar plants. It is based on the idea of preference relations and Pareto dominance and, avoiding to operate an inter-comparison of different locations' attributes, it can be considered as assumptions-free.

The second part of the paper applies such filtering method to Italy, a country with relatively high potentials in terms of solar energy that, however, currently lacks an optimal site selection analysis. Once applied, the filter reduces the original set of feasible locations by more than 99%. The resulting Pareto efficient locations, evaluated through five selected criteria, are concentrated in the southern part of Italy and, particularly, in the islands of Sicily and Sardinia.

Keywords: Geographic Information System; optimal site selection; Pareto dominance; renewable energy sources; solar energy.

J.E.L.: Q01; Q24; Q42.

Introduction

Although fossil fuels are still, by far, the principal source for meeting the growing demand of energy worldwide, the share of renewable resources in energy production is steadily growing [Twidell and Weir, 2015]. The increasing environmental concerns for global worming caused by greenhouse gases (GHG) emissions and the likely rise of fuel prices the more this resource will move closer to depletion are all elements that suggest a further expansion in the use of renewable energy sources (RES) in the future. These lasts are defined, according to the EU Directive 2009/28/EC, as: wind, solar, aerothermal, geothermal, hydrothermal and ocean energy, hydropower, biomass, landfill gas, sewage treatment plant gas and biogases. All together, they have the potential to theoretically exceed by several folds the world demand of energy even for extremely energy intensive scenarios [Ellabban et al., 2014]. For all these reasons, it is expected that, in 2035, the level of electricity generated through RES will be almost triple compared to the 2010 level [Ellabban et al., 2014].

One of the initial barriers to the diffusion of RES was their relatively high costs translating into a non-competitive output price [Sims et al., 2003]. This, however, has dramatically changed for several RES. The cost of solar panels, for example, decreased by 60% during the period 2008-2010 [Grossmann et al., 2013]. Grid parity, defined as the lifetime generation cost of electricity from an unconventional resource being comparable with the electricity price of conventional sources on the grid [Branker et al., 2011], is generally considered as the threshold able to boost the diffusion of a new energy source [Yang, 2010]. According to several papers, solar and wind energy have already reached or are very close to reaching grid parity in several countries [Bhandari and Stadler, 2009; Breyer and Gerlach, 2013; Khare et al., 2013; Karakaya et al., 2015; Yao et al., 2015]. This fact, however, is not commonly accepted: Lund [2011], for example, predicts the attainment of grid parity in 2027 for wind energy and in 2035 for Photovoltaic (PV) energy. Despite this discrepancy, mainly due to a lack of standardization in the operational definition of grid parity, it seems fairly accepted that the share of RES, among which solar and wind are the most diffused, is destined to significantly grow, even if the subsidies from which they are currently benefiting in several countries will be reduced or completely eliminated [Grossmann et al., 2013].

If solar and wind are the two prominent sources in the set of RES, the former seems to have more chances of becoming the real alternative to fossil fuels in electricity generation. In fact, it has been estimated that its technical potential is approximately 420 TW, whereas all the other RES together cannot generate more than 4.4-75.6 TW [Lewis, 2007; Grossmann et al., 2013]. If solar panels for meeting households' or single firms' energy needs have the possibility to be installed directly on buildings, large-scale solar plants, either Photovoltaic (PV) of Concentrated Solar Power (CSP) systems, require a relatively large amount of space and an ad-hoc site. The problem of site selection becomes then central, either because land is another fundamental environmental and economic resource and because the selection of a site is a significant determinant of the final cost of solar energy [Sánchez-Lozano et al., 2014].

The problem of site selection for energy producing plants is a well recognized topic as testified by the high number of papers mentioned in the literature review of Pohekar and Ramachandran [2004]. One of the most problematic aspects is the fact that such decision entails considering several dimensions whose inter-comparability is almost impossible given the different nature of their units of measure [Jun et al., 2014]. Although it could be argued that this decision is mainly economic; social, environmental and distributive aspects necessarily enter into the picture. The possibility to translate into monetary terms such aspects, despite theoretically viable, is often prevented by the lack of appropriate data. Multi-Criteria Decision Making (MCDM) techniques have been seen as an effective tool in order to obviate this problem [Pohekar and Ramachandran, 2004]. However, they also have their drawbacks, either because the assumptions operated by these procedures in order to allow for the inter-comparison of criteria influence the final result and because, in presence of large territories and a high number of criteria, the computational burden may become prohibitive.

The present paper presents a very simple and fast method to select a subset of all possible locations where solar plants could be installed. Beyond simplicity, the strength of this method stays in the almost total lack of assumptions required to operate an inter-comparison of different dimensions. Actually, the method does not operate any inter-comparison at all, allowing for a very "safe" and neutral result. Although this does not generally guarantee to obtain neither a unique nor a sufficiently small set of feasible locations, through an application to the Italian territory, it is shown that its discriminating power could be very strong, allowing to obtain a sufficiently small set of locations over which further analysis can be performed. Beyond its theoretical content, the paper is, to the best of our knowledge, the first attempt to perform an optimal site-selection analysis for solar plants focused on the whole Italian territory.

Section 1 provides a review of the relevant literature, Section 2 describes the method whereas Section 3 presents its application to Italy. Finally, Section 4 is devoted to conclusions.

1 Review of the Relevant Literature

As mentioned before, the environmental debate and the possibility of rising prices of exhaustible resources have prompted a strong academic focus toward RES in the last two decades. The problem of site selection for the installation of energy generating plants can be seen as a specific subfield of this literature that has gained an analogous momentum in the same period. Either wind and solar power have been the object of this type of analysis. Both have benefited by the production of databases, models and softwares providing geographical information on key aspects, such as wind speed or solar irradiance, for assessing the potential generating capacity of different locations. Examples are Troen and Petersen [1989]; Scharmer and Greif [2000]; Ding et al. [2005]; Šúri et al. [2005] and Huld et al. [2012].

GIS-based (Geographical Information System) MCDM techniques have been widely used for optimal site selection of various RES plants. Goumas et al. [1999]; Goumas and Lygerou [2000] and Haralambopoulos and Polatidis [2003] proposed this methodology for geothermal site selection. Optimal location of wind farms has been investigated by Baban and Parry [2001]; Tegou et al. [2010]; Mari et al. [2011]; Van Haaren and Fthenakis [2011]; Gorsevski et al. [2013]; Mekonnen and Gorsevski [2015] and Latinopoulos and Kechagia [2015]. A similar analysis, but focused on solar plants, has been carried on by Carrión et al. [2008b,a]; Aragonés-Beltrán et al. [2014]; Sánchez-Lozano et al. [2014] and Tahri et al. [2015]. Finally, Aydin et al. [2013] and Jun et al. [2014] evaluated the location of hybrid systems, as to say generating power plants relaying on more than a single energy source, focusing on solar-wind plants.

Despite varying in the object of the study, in the location of interest and in the specific methodology adopted, all the mentioned studies have two common elements. The first is the use of an MCDM technique. According to Pohekar and Ramachandran [2004], MCDM can be divided into two main subcategories: Multi-Objective Decision Method (MODM) and Multi-Attribute Decision Method (MADM). Whereas the first category is adopted when there are no predetermined alternatives but rather objectives functions with set of constraints whose simultaneous optimization may be conflicting, the latter, instead, entails the choice between a set of alternatives with multi-attributes that are hard to quantify and to compare [Pohekar and Ramachandran, 2004]. The site selection problem can be ascribed to the second category since the alternatives, the locations where a plant can be set, are predefined.

Three MCDM methodologies are generally adopted in RES site selection problems. The Analytical Hierarchy Process (AHP), presented in Saaty [1990] and Saaty [2008], divides hierarchically the problem to be solved into a general goal, criteria, sub-criteria and, finally, the alternatives. At each level of the hierarchy, its elements are compared pairwise according to their importance, valued through a predefined scale, with respect to the element at the next level of the hierarchy. The results of this pairwise comparison are inserted into a matrix that is subsequently multiplied to the weight attributed to the element at the next hierarchy level used as the reference point in the benchmarking. This process allows to form a whole set of weights for each element in the hierarchy accounting for its relative importance in reaching the final goal. The alternative with the highest weighted score will then be the preferred one [Pohekar and Ramachandran, 2004].

The elimination and choice translating reality (ELECTRE) method, proposed by Roy [1990], is another popular selection mechanism in the present domain. It uses the concept of outranking in order to evaluate the attributes of the alternatives, through a pairwise comparison, and an index of credibility to evaluate the outranking robustness. It requires the attribution of weights assessing the importance of each attribute and it selects the alternatives that perform better in most criteria without being extremely poor in neither of them. Being the resulting order not necessarily complete, the preferred alternative could not be unique but rather a set [Pohekar and Ramachandran, 2004].

The last method that worth to be mentioned is PROMETHEE (preference ranking organization method for enrichment evaluation), introduced by Brans et al. [1986]. This method too relies on the idea of outranking, and of being outranked, to evaluate the suitability of an alternative together with a pairwise comparison by means of preference functions. It uses threshold values to distinguish between indifference and strict preference and it relies on the exogenous assignment of weights to assess the importance of each attribute. The selected alternative is the one having the highest weighted difference between outranking and outranked values [Pohekar and Ramachandran, 2004].

Among the papers mentioned before, Carrión et al. [2008b]; Tegou et al. [2010]; Uyan [2013] and Tahri et al. [2015] adopt the AHP method, whereas Aragonés-Beltrán et al. [2014] proposes a methodological modification of this method combining it with Analytic Network Process. Van Haaren and Fthenakis [2011] uses a hierarchical method although without a weighting of attributes. Sánchez-Lozano et al. [2014] adopts the ELECTRE-TRI method whereas Haralambopoulos and Polatidis [2003] PROMETHEE-II. Gorsevski et al. [2013] and Mekonnen and Gorsevski [2015] prefer to use a participatory mechanism, adopting the Borda method, with weights being given according to the participants preferences, to rank sites. Mari et al. [2011] formulates a DSS (decision support system) in the form of a web-application with map layers representing different attributes and Latinopoulos and Kechagia [2015] creates a suitability index through boolean operations and weighted attributes. Although not mentioned, the TOPSIS and VIKOR methods, both relying on the Euclidean distance of a vector of weighted attributes from an ideal attributes vector (choice), have also found application in site selection. In fact, they have been respectively adopted by Choudhary and Shankar [2012] and Kaya and Kahraman [2010].

The other element being in common among the great majority of the papers focusing on RES plants' site selection is the territorial extension taken into consideration. It is generally below the national level, sometimes being confined to the municipality or, at most, the regional level. Kaya and Kahraman [2010] consider the city of Istanbul, Van Haaren and Fthenakis [2011] the State of New York, Gorsevski et al. [2013] and Mekonnen and Gorsevski [2015] a portion of Ohio: its northern part the first and Lake Eire the latter. We can continue mentioning Haralambopoulos and Polatidis [2003] and Tegou et al. [2010] whose analysis focus on single islands of Greece; Mari et al. [2011] study the region of Tuscany, in Italy, whereas Aydin et al. [2013] and Uyan [2013] consider specific regions of Turkey. Finally, Carrión et al. [2008b] and Sánchez-Lozano et al. [2014] narrow their attention to Spanish sub-regions and Tahri et al. [2015] to the southern Morocco. Some exceptions are Choudhary and Shankar [2012], considering India, and Jun et al. [2014], considering China, that, however, compare few regions rather than specific territorial units where to physically build a plant. Finally, it must be mentioned the paper of Castillo et al. [2016], the real exception to the trend of focusing on areas below the national scale, that assesses the whole territory of the EU-28.

2 A filtering method for the site selection of large scale solar plants

As seen in the previous section, there are several methods for site selection of RES plants that are well established and went through years if not decades of refinement and improvements. However, these methods are particularly suited to evaluate alternatives characterized by a relatively large number of attributes. Once moving up on the territorial scale taken into consideration, it becomes more difficult to obtain reliable data over several indicators covering the whole area. Furthermore, as noted by Choudhary and Shankar [2012], ELECTRE is a computational complex method, while the pairwise comparison operated by AHP becomes a cumbersome procedure as the number of alternatives grow. By analogy, this could be extended to PROMETHEE. Obviously, considering a larger territory necessarily entails to increase considerably the number of alternatives, as to say the number of potential locations for plant installation.

Therefore, it seems opportune to have a method for reducing the complexity of the problem once a large territory is taken into consideration. Such method could take the form of a filter to make a preliminary skim in order to eliminate less suitable places. The MCDM analysis, with the methods previously described, could then be applied to the subset of remaining locations, thus reducing the computational and the data collection complexity. Ideally, the filter should take into account few attributes, it should avoid eliminating potentially suitable locations but it should also possess a sufficiently high discriminating power in order for its application to be meaningful. Objectivity is another desiderata to be taken into account.

2.1 Preliminary definitions

Consider to have a finite set $L = \{l_1, l_2, ..., l_n\}$ of n potential locations for setting a plant. When creating a suitability map using GIS software, as generally done in the previously mentioned literature, such locations could correspond to the cells of a vector layer or to the pixels of a raster layer. Suppose further to have a set of m attributes $X = \{x_1, x_2, ..., x_m\}$. For each attribute, there exists an ordinal scale that allows to compare two locations according to that specific attribute. Let us indicate with $p_{i,j}$ the ordinal value associated to location l_i for attribute x_j, with $i = 1, 2, ..., n$ and $j = 1, 2, ..., m$. This implies that there exists a well defined preference relation over each attribute possessed by locations. Furthermore, locations can be compared among each other with regard to the degree of possession of a certain attribute:

$$
\begin{aligned}
& l_a(x_j) \succeq l_b(x_j) \vee l_b(x_j) \succeq l_a(x_j). \\
& (l_a(x_j) \succeq l_b(x_j) \wedge l_b(x_j) \succeq l_a(x_j)) \Leftrightarrow l_a(x_j) \sim l_b(x_j).
\end{aligned}
$$

This reads that location l_a is preferred to location l_b in terms of attribute x_j or vice-versa, and, if both statements are true, the two locations are indifferent, or else, equally desirable, according to attribute x_j. The degree of possession of an attribute can be measured either in terms of numerical or qualitative values. As stated, however, $p_{i,j}$ is a numerical value required to translate the preference operators – $\succeq, \preceq, \sim$ – into the order operators $\geq, \leq, =$. In particular, if the degree of possession of an attribute is described by a qualitative indicator – e.g. "very good", "good", etc. – p serves to translate such indicators into a numerical ordering.

In case the degree of possession of an attribute is already a numerical value – e.g. the average radiative force of a location, its distance from the electricity grid, etc. – the value $p_{i,j}$ can simply be such numerical value for location l_i. This, however, do not imply that preference operators can be substituted by order operators. In fact, although two numerical values may differ, such difference could not be sufficient to justify a preference shift. We can therefore write:

$$
\begin{aligned}
& l_a(x_j) \succeq l_b(x_j), \quad \text{if} \quad (p_{a,j} + q \geq p_{b,j}). \\
& l_b(x_j) \succeq l_a(x_j), \quad \text{if} \quad (p_{b,j} + q \geq p_{a,j}). \\
& l_a(x_j) \sim l_b(x_j), \quad \text{if} \quad (p_{a,j} + q \geq p_{b,j}) \wedge (p_{b,j} + q \geq p_{a,j}). \\
& l_a(x_j) \succ l_b(x_j), \quad \text{if} \quad (p_{a,j} + q \geq p_{b,j}) \wedge \neg(p_{b,j} + q \geq p_{a,j}). \\
& l_b(x_j) \succ l_a(x_j), \quad \text{if} \quad (p_{b,j} + q \geq p_{a,j}) \wedge \neg(p_{a,j} + q \geq p_{b,j}).
\end{aligned} \tag{1}
$$

The newly introduced parameter q can be regarded as a numerical threshold beyond which a preference shift occurs. It is the decision maker that has the possibility to set such value and nothing prevents her to adopt a complex function rather than a simple parameter.

There is a last important clarification to be made. In (1) it is described the case of a desirable attribute, meaning that a location will be more desirable the higher is the level of possession of such attribute. Obviously, attributes can also be undesirable. For example, the higher is the agricultural productivity of a portion of land, the lower will be its suitability as a solar field.[1] In presence of

[1] Note that the desirability of an attribute must be evaluated in relation to the objective of the analysis. Clearly, a high agricultural productivity is generally considered a desirable attribute for a land parcel, but not if the objective is to use such parcel for installing a solar plant.

an undesirable attribute, (1) must be changed into:

$$\begin{aligned}
&l_a(x_j) \succeq l_b(x_j), \quad \text{if} \quad (p_{a,j} \leq p_{b,j} + q).\\
&l_b(x_j) \succeq l_a(x_j), \quad \text{if} \quad (p_{b,j} \leq p_{a,j} + q).\\
&l_a(x_j) \sim l_b(x_j), \quad \text{if} \quad (p_{a,j} \leq p_{b,j} + q) \wedge (p_{b,j} \leq p_{a,j} + q).\\
&l_a(x_j) \succ l_b(x_j), \quad \text{if} \quad (p_{a,j} \leq p_{b,j} + q) \wedge \neg(p_{b,j} \leq p_{a,j} + q).\\
&l_b(x_j) \succ l_a(x_j), \quad \text{if} \quad (p_{b,j} \leq p_{a,j} + q) \wedge \neg(p_{a,j} \leq p_{b,j} + q).
\end{aligned} \tag{2}$$

Finally, note that we are assuming the desirability of an attribute to be constant. This is quite a strong and unsafe assumption. Let us consider the following example remaining in the domain of site selection for solar farms. Suppose to have to select a site whose aim is to provide energy to a city. Clearly, the closer the site to the city, the lower are the energy transportation costs. Distance can therefore be regarded as an undesirable attribute. However, a solar farm very close to an urban area could also have negative consequences. Therefore, till a certain threshold, distance could be a desirable property. As this example shows, desirability may change according to the level of the same attribute. This problem, although relevant, will be here disregarded since, in our practical application, there are no attributes of this type.

2.2 The filtering method

The filtering method we will adopt is based on the idea of Pareto efficiency. Simply, all the strictly dominated locations will be eliminated in order to end up with the set of strict Pareto efficient locations. Let us recall the formal definition of Pareto frontier. Define X as a compact set of decisions in $\mathbb{R}^n$ and Y as the set of criteria vectors in $\mathbb{R}^m$, assuming that the preferred directions of criteria values are known. Consider then a system with function $f : \mathbb{R}^n \mapsto \mathbb{R}^m$, such that $Y = \{\boldsymbol{y} \in \mathbb{R}^m | \boldsymbol{y} = f(\boldsymbol{x}), \boldsymbol{x} \in X\}$. The Pareto frontier, $P(Y)$, is the set of strictly un-dominated points. A point $\boldsymbol{y}' \in \mathbb{R}^m$ is said to strictly dominate another point $\boldsymbol{y}'' \in \mathbb{R}^m$ if $\boldsymbol{y}' \succ \boldsymbol{y}''$ implying $y'_i \succeq y''_i, i = 1, 2, ...m$, with strict preference ($\succ$) holding for at least one criterion. Therefore $P(Y) = \{\boldsymbol{y}' \in Y | \{\boldsymbol{y}'' \in Y | \boldsymbol{y}'' \succ \boldsymbol{y}', \boldsymbol{y}'' \neq \boldsymbol{y}'\} = \emptyset\}$.

If we define as L the set of locations to be evaluated according to our selected m attributes, what we want to obtain is $P(L)$, in order to exclude all the locations that are Pareto dominated. Through (1) and (2) we have a simple way for translating preference relations into order relations that are mathematically tractable. In order to make such filter operational, once having defined as L the ordered set of locations $l_1, l_2, ..., l_n$ with index set $\mathcal{N}$, define as $P \in \mathbb{R}^{n \times m}$ the matrix defining the degree of possession of each attribute by each location. Let us further divide P into $P^d \in \mathbb{R}^{n \times g}$ and $P^u \in \mathbb{R}^{n \times h}$, being, respectively, the matrix collecting desirable and undesirable attributes. Clearly, $g + h = m$. Finally, denote with $\boldsymbol{q} \in \mathbb{R}^g$ and with $\boldsymbol{w} \in \mathbb{R}^h$ the vectors of threshold values for, respectively, the desirable and undesirable attributes. Denote with $\mathcal{D}$ and

$\mathcal{U}$ the sets of, respectively, desirable and undesirable attributes. We then have:

$$\begin{aligned} P(L) = \{ & l_i | \nexists l_z : p^d_{z,j} + q_j \geq p^d_{i,j}, \forall j \in \mathcal{D} \wedge \neg (p^d_{i,j} + q_j \geq p^d_{z,j}, \forall j \in \mathcal{D}) \\ & \wedge\ p^u_{z,s} \leq p^u_{i,s} + w_s, \forall j \in \mathcal{U} \wedge \neg (p^u_{i,s} \leq p^u_{z,s} + w_s, \forall j \in \mathcal{U}), \\ & \forall z \neq i \in \mathcal{N}, \forall i \in \mathcal{N} \} \,. \end{aligned} \tag{3}$$

In the Appendix, it can be found a Python code snippet showing the function for obtaining $P(L)$. It must be noted that, if $\boldsymbol{q} = \boldsymbol{0}$ and $\boldsymbol{w} = \boldsymbol{0}$, with $\boldsymbol{0}$ being a vector with all zero elements, $P(L)$ is identical to the set of efficient locations that would be obtained by adopting Free Disposable Hull (FDH) and setting the desirable attributes as outputs and the undesirable ones as inputs. In Bardhan et al. [1996], in fact, the decision making unit (DMU) o, name that indicates the subjects whose efficiency is evaluated, is considered efficient under FDH if $\nexists k : \boldsymbol{y}_o \leq \boldsymbol{y}_k \wedge \boldsymbol{x}_o \geq \boldsymbol{x}_k, \forall k \neq o \in D$, with at least one inequality holding strictly for one vector component. D is defined as the set of DMUs, $\boldsymbol{y}$ as the outputs vector and $\boldsymbol{x}$ as the inputs vector. Apart for the notational differences, this is clearly the same definition as (3).

3 An Application to Italy

Once having defined the filtering method to be adopted, it will be tested on the Italian territory. Although Italy is one of the leading countries in the world in terms of solar energy production – fifth for installed capacity and third with regard to the share of electricity produced through solar power in 2017 [Jäger-Waldau, 2017] –, to the best of our knowledge, there is no study specifically focused on this country that tackles the problem of site selection for solar plants.

Apart from the filtering method, there are other methodological considerations that worth to be mentioned. In order to conduct the analysis, the whole Italian territory has been subdivided into cells of 1×1 kilometres – an area of 100 hectares –, that is the area of a medium-large scale solar plant. Note that the largest solar plant in Italy, the Montalto di Castro photovoltaic power station, occupies an area of, approximately, 166 ha. Cells with an area lower than this value have been dropped together with all small islands. The second step consists in applying a preliminary filter to exclude all areas that are clearly unsuitable. Following Castillo et al. [2016], areas with more than a 30% slope have been judged as technically unfeasible together with water bodies. Furthermore, inhabited or, more generally, areas with anthropogenic components excluding the ones related to agriculture have also been masked out. Additionally, given that electricity generation through solar energy has a well recognized environmental aim, natural protected areas, wetlands and areas of natural interests have been excluded too. Slope data have been obtained by elaborating, with the open-source software QGIS (version 2.18), the 40 meters Digital Terrain Model (DTM) [Link] provided by the Italian Ministry of Environment. The Corine Land Cover (CLC) map, year 2012, [Link] has been used to derive data about water bodies and built areas. Natural protected areas have been retrieved from the World Database on Protected Areas (WDPA) [Link] and by the map of wetlands of international interest (RAMSAR) [Link]. In Figure 1 it is possible to see all the maps used as masks in order to exclude all the alleged unsuitable areas.

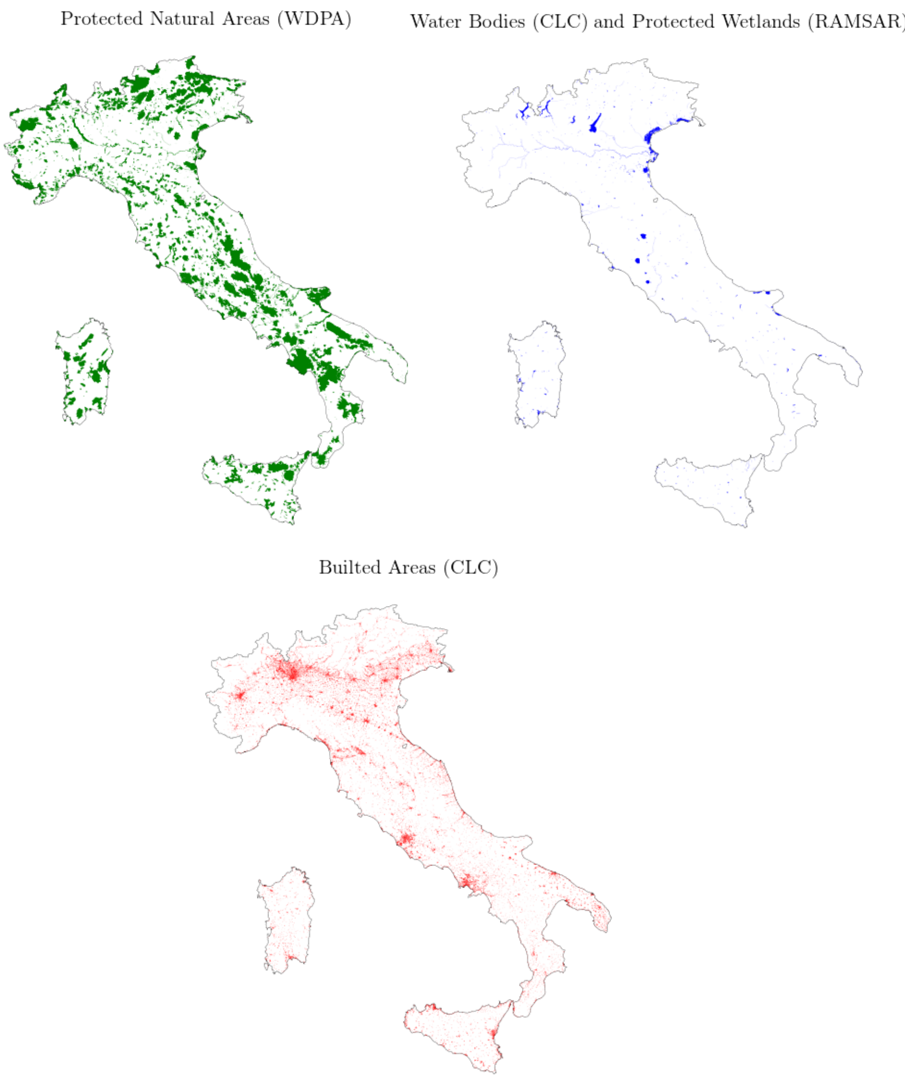

Figure 1: Mask Maps for Excluded Areas

3.1 The choice of the relevant attributes

Once excluded all the mentioned areas and after having eliminated all the remaining cells with an area lower than 100 ha, we are left with 47662 potentially

All Feasible Locations

Figure 2: Map of Feasible Locations

suitable locations, shown in Figure 2. The selection of the relevant attributes to consider when applying the mentioned filtering method is a crucial step. By the very nature of Pareto dominance, the higher is the number of attributes chosen, the lower will be the discriminating capacity of the filter. This calls for a relatively low number of attributes. Nonetheless, if very relevant attributes are omitted, and maybe used in a subsequent analysis, this may cause some potentially promising locations to be excluded. The abundant production on this field and a recent paper of Chen et al. [2014] that explicitly analyses the relevance of different criteria for solar plants site selection offer the possibility to make a well reasoned choice.

According to Chen et al. [2014], solar radiation is the most important attribute and this comes with no surprise being, in fact, a criterion adopted by almost all studies of this type. The present paper uses monthly average global irradiance on a horizontal surface (W/m^2) data provided through PVGIS [Huld et al., 2012]. These monthly averages are calculated on the base of hourly data for the period 2005-2015. Given the relatively long time span, this value should be able to get rid of the bias produced by exceptional years for specific locations. In order to have a unique value for each cell, yearly means have been adopted and, subsequently, the average value for each cell has been computed. Although mean temperature is the second attribute for importance mentioned by Chen et al. [2014], it is another climatic attribute strongly correlated with solar radiation and, therefore, it has been judged as more suitable for a second stage analysis.

Orography is also mentioned as an important field in Chen et al. [2014], with slope being its prominent criterion. Besides excluding lands with slope higher than 30%, this attribute has also been included in the Pareto dominance filtering by computing the average slope of each cell. Area and orientation, the other two orography criteria mentioned by Chen et al. [2014], have been excluded being of minor importance.

Distance to the electricity grid, although downgraded to minor criterion by the analysis of Chen et al. [2014], has been considered by several studies, among which Janke [2010]; Uyan [2013]; Sánchez-Lozano et al. [2014] and Castillo et al. [2016]. We have therefore decided to include it. The Italian electricity grid map has been obtained from the Italian Ministry of Environment [Link]. Only transmission lines with a capacity of, at least, 220 kilovolts (Kv) have been considered and distance has been computed as the minimal distance between a cell centroid and the closest transmission line. Since Italy has few large uninhabited areas and these are mostly concentrated in mountainous areas largely excluded by the slope filtering, distance to roads has been judged as a minor concern although several papers – Janke [2010]; Uyan [2013]; Sánchez-Lozano et al. [2014] and Castillo et al. [2016] – adopt this attribute. The relatively large area of the considered cells further justifies the exclusion of this attribute.

The competing effect of medium-large scale solar plants with other possible land uses is another well recognized problem and, consequently, it is often translated into a selection criterion. Agriculture plays a central role on this regard with several authors adopting indicators of agricultural marginality as desired attributes. Often, however, they need to rely on indirect and potentially scarcely informative indicators. Castillo et al. [2016], for example, adopts three indicators: erosion, salinity and soil contamination with metals as proxy for agricultural marginality. Thanks to the recent work of Sallustio et al. [2018], it is possible to have, for Italy, a much more direct indicator: the average value of agricultural land (AVAL). The authors provide a map where land is divided into 5 categories of value shown in Table 1. The last attribute adopted is rather

Table 1: **Categories of Average Land Value for the Italian Territory**

Ordinal Category	AVAL (€$\times$ha^{-1})
1	<2000
2	2000-7000
3	7000-12000
4	12000-25000
5	>25000

This Table partially reproduces Fig. 3 in Sallustio et al. [2018].

unusual in this type of analysis. It is the number of hotels and restaurants per square kilometre retrieved from the map of Italian Landscapes Features produced by the Italian Ministry of Environment. This indicator is used as a proxy of either the degree of urbanization of a location and of its touristic value. Since we are not focusing on solar plants specifically designed to provide energy to a urban district, but rather connected to the national grid, the distance from densely inhabited areas is a desideratum. Furthermore, given the relatively high contribution of the touristic sector to the Italian GDP – with a rough estimation of almost 5% in 2017 according to the World Travel and Tourism Council –, marginally valuable touristic locations are clearly preferable for solar plant installation. Although this indicator might be far from being a perfect proxy for both dimensions, it condenses in a single attribute both aspects and it tries to encompass a dimension generally overlooked. The values of the five selected attributes for the feasible locations are represented in Figure A1 in Annexes.

3.2 Pareto Efficient Locations

Resuming the last section, five attributes have been selected: yearly average solar irradiance, percentage slope, average value of agricultural land, distance to electric lines and the number of restaurants and hotels per square kilometer as a proxy of touristic value and population density. Of these, AVAL is the only attribute with an ordinal scale whereas solar irradiance is the only desired attribute.

In the application of the mentioned filtering method, the threshold values – the values of the $\mathbf{q}$ and $\mathbf{w}$ vectors in the theoretical presentation – have all been set to zero. This maximizes the discriminating power of the filter at the cost of eliminating locations that may be very close to the efficient frontier. Once applied the filter, of the 46592 locations judged as suitable[2], 303 lay on the Pareto Frontier. They are shown in Figure 3. First of all, it must be noted the strong discriminating power of the Pareto dominance method that eliminates more than 99% of feasible locations. If the final set of efficient locations is considered too narrow, the introduction of thresholds for, at least, some of the attributes, would help to enlarge it. From Figure 3, it is possible to observe that the Pareto dominant plots are concentrated in few regions. Sicily plays the lion's share with 229 locations, followed by the other Italian major island, Sardinia, with 29 and by other two souther regions: Basilicata (15) and Campania (12). In the northern area, only seven locations lay on the efficient frontier, of which five are located in the western part of Piedmont, in the middle of the mountainous chain of Alps. It may be questioned that these are effectively optimal locations for solar plants and, in fact, they are on the frontier due to their very low values on two attributes: AVAL and number of hotels and restaurants. This testifies how a further analysis may be necessary, possibly with the inclusion of

[2]The feasible locations are 47662, but 1070 have been dropped due to missing values in some of the attributes.

Figure 3: Map of Pareto Efficient Locations

further attributes and techniques to weight them. However, the dimensionality of the problem at hand is considerably reduced, fastening therefore any further step.

There are three last considerations that are worth to be made. First, although the most of feasible locations are in the northern Po valley, only two of such plots turn out to be efficient. This result is driven mainly by the lower level of solar irradinace in the North of Italy compared to the South and by the high values of AVAL in this area – maximal for almost all plots – since it is one of the most fertile regions in the whole country. Secondly, efficient locations, being concentrated in southern regions, enjoy higher levels of solar irradiance, the most important attribute according to Chen et al. [2014]. Third, the relatively high number of efficient plots in Sardinia is an important and positive result given the high costs to bring energy to such region.

4 Conclusions

The present paper has presented a filtering method based on the idea of Pareto dominance for optimal site selection of solar plants. In particular, the filter serves to reduce the dimensionality of the problem by trimming the number of feasible locations to be examined and can be adopted for RES other than solar energy. In particular, the paper has presented a simple way to translate preference relations into order relations in order to algorithmically operationalize the Pareto dominance criterion. By avoiding to operate any inter-comparison between different attributes, such method can be considered as safe from potentially harmful assumptions.

Through an application to Italy, it has been shown that the proposed filter can have a very strong discriminating power since, over the more than 45000 locations judged as feasible after a first elimination phase, only 303 result to be Pareto efficient. Such outcome has been obtained by taking into consideration five key attributes retrieved from a literature review: solar irradiance, average slope, distance to electricity grid, average value of agricultural land and number of hotels and restaurants as a proxy for population density and touristic value. The Pareto efficient locations are mainly located in the southern part of Italy, where solar irradiance is higher, and, particularly, in the two major islands of Sicily and Sardinia.

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Annexes

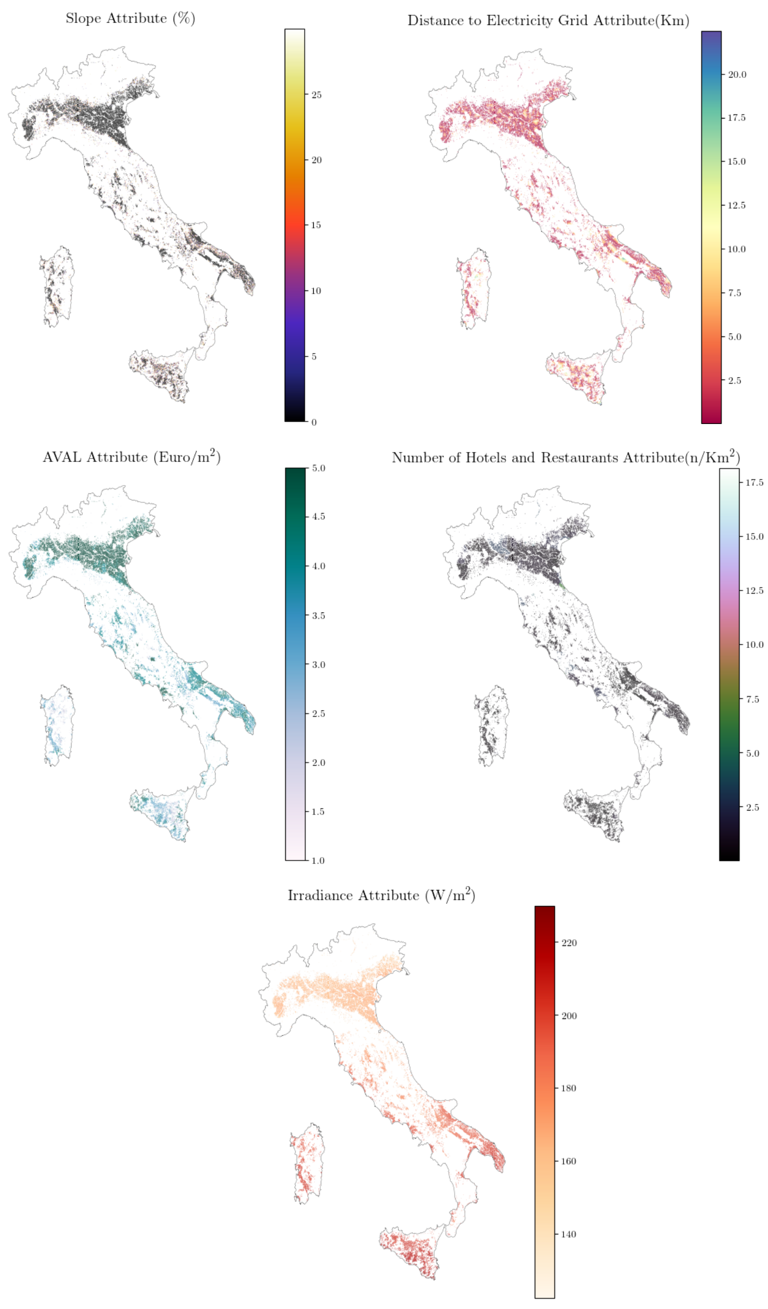

Figure A1: Attributes Values of Feasible Locations

Python (version 3.6) code snippet for retrieving Pareto efficient locations

```
# feas_loc is a geopandas GeoDataFrame of feasible
                            locations
# The 5 selected attributes in feas_loc are:
# Solar irradiance:                 sol_year_m
# Average slope:                    slope_m
# AVAL:                             aval_m
# Distance to electricity grid:     el_dist
# Number of hotels and restaurants: nhr_m

# List of desirable attributes
at_d = [[feas_loc['sol_year_m'][i]] \
        for i in range(len(feas_loc))]

# List of undesirable attributes
at_und = [[feas_loc['slope_m'][i],\
           feas_loc['aval_m'][i], \
           feas_loc['el_dist'][i],\
           feas_loc['nhr_m'][i]]  \
          for i in range(len(feas_loc))]

# Vectors of threshold values
q = [0]
w = [0,0,0,0]

# Function to individuate Pareto dominated locations
def p_d_l(at_d, at_und, q, w):
    '''Function to compute Pareto dominated
    locations given a list of desirable attributes
    (at_d) and one of undesirable attributes (at_und)
    and their respective vectors of threashold
    values (q and w)'''
    par_dom = []
    for i in range(len(at_d)):
        ad = at_d[:i] + at_d[i+1:]
        au = at_und[:i] + at_und[i+1:]
        for g in range(len(ad)):
            if all([at_d[i][j] + q[j] <= ad[g][j] \
            for j in range(len(q))]) \
            and all([at_und[i][j] >= au[g][j] + w[j] \
            for j in range(len(w))]):
                par_dom.append(i)
                break
    return par_dom
```

```
# Pareto efficient locations
eff_l = feas_loc.drop(feas_loc.index \
                      [p_d_l(at_d,at_und, q, w)])
```