Assessment of a weather-based climate classification with building energy simulation

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Abstract

In this research, we performed extensive building energy simulations to assess the representativeness of a methodology for climate clustering and representative climate identification, previously proposed by the authors and applied, as an example, to a dataset of more than 300 European climates. Descriptive and non-parametric statistics were exploited to discuss the suitability of the methodology for selecting a limited number of representative climates to run building energy performance analyses at European scale. While for the characterization of space heating performance all representative climates were found necessary for assessments at continental scale, simplifications were found applicable for space cooling.

Key Innovations

- Building energy simulation was adopted to discuss the results of a weather based-climate classification.
- Statistical tests were performed to identify differences and overlapping among the simulated building energy performance.
- The tested weather-based classification was found suitable for the analysis of space heating demands at European scale, but simplifications can be applied in case the focus is put on cooling demands.

Practical Implications

The definition of energy policies at national or at European scale has to cope with a variety of climate conditions and the current main climate classifications are not developed specifically to address building energy performance issues. With this work, we assess a weather-based classification previously proposed by the authors with the aim to provide recommendations regarding its applicability for building energy performance analyses.

Introduction

According to the Energy Performance of Buildings Directive (EPBD) 2018/844/EU, a high-performance and smart building is supposed to "*maintain energy performance and operation [...] through the adaptation of energy consumption*", "*adapt its operation mode in response to the needs of the occupant*" and show "*flexibility and load shifting capacities*". These performance requirements entail a particular attention to the external weather conditions, especially for the definition of national targets for the Member States of the European Union. In this context, climate classification can play a significant role to minimize errors and improve representativeness.

Many alternative climate zoning techniques are available in the literature and most of them are weather-based climate classifications, i.e., based on the analysis of quantities such as degree-days, air temperature and precipitation data. However, there is no general consensus in the scientific community about which one should be used and, consequently, the obtained outputs can be conflicting (Walsh *et al.*, 2017a and 2017b). Furthermore, although some classification systems, e.g., the Köppen-Geiger system (Peel *et al.*, 2007) and the ASHRAE 169 classification (ASHRAE, 2020), are adopted more frequently than others, some researches outlined limitations and expressed the need for new or modified solutions (Walsh *et al.*, 2017a). For instance, Bai *et al.* (2020) found that the ASHRAE classification is not able to distinguish the climatic features of some Chinese regions and proposed a new classification based on clustering techniques. Similarly, Yang *et al.* (2020) developed a supervised classification algorithm and used the Mahalanobis distance to discuss similarities among Chinese climates.

In previous contributions (Pernigotto and Gasparella, 2018; Pernigotto *et al.*, 2019), the authors proposed a weather-based method for climate zoning and identification of representative climates, based on data-mining techniques and statistical analyses. Differently from traditional approaches, all weather quantities relevant to the building energy balance were accounted for, in order to enhance robustness and representativeness of the results in the context of building energy performance analyses at national or continental scale. In the current research, the representative climates previously obtained applying the proposed procedure to a test dataset of more than 300 European locations were analysed to discuss their suitability for continental building energy performance analyses. In this context, similarly to other approaches in the literature (Walsh *et al.*, 2018), extensive building performance simulations were exploited to validate the proposed method for climate zoning and to identify potential further simplifications.

Methods

Analysed classification and representative climates

Pernigotto *et al.* (2019) proposed a new approach for weather-based climate clustering and representative climate identification, assuming typical years as a good approximation of long-term trends. As an example, it was applied to an open dataset of 318 European climates available in the EnergyPlus online weather database (https://energyplus.net/weather) or national sources, as the database of reference years published in 2016 by the Italian CTI (Comitato Termotecnico Italiano, https://try.cti2000.it/). 7 groups were obtained and 12 representative climates identified (Figure 1 and Table 1). Except for class 1, including just two alpine climates, Kasprowy Wierch and Sniezka (Poland, close to the border with Czech Republic), at least a representative climate was selected for each class. Besides classes 2 and 4, represented respectively by Tampere (Finland) and Koln (Germany), the remaining classes have more than one representative climate: Ljubljana (Slovenia) and Czestochowa (Poland) are the representative climates for class 2, Milan, Lodi and Varese (Italy) for class 5, Madrid and Huesca (Spain) for class 6, and Caserta, Latina and Oristano (Italy) for class 7.

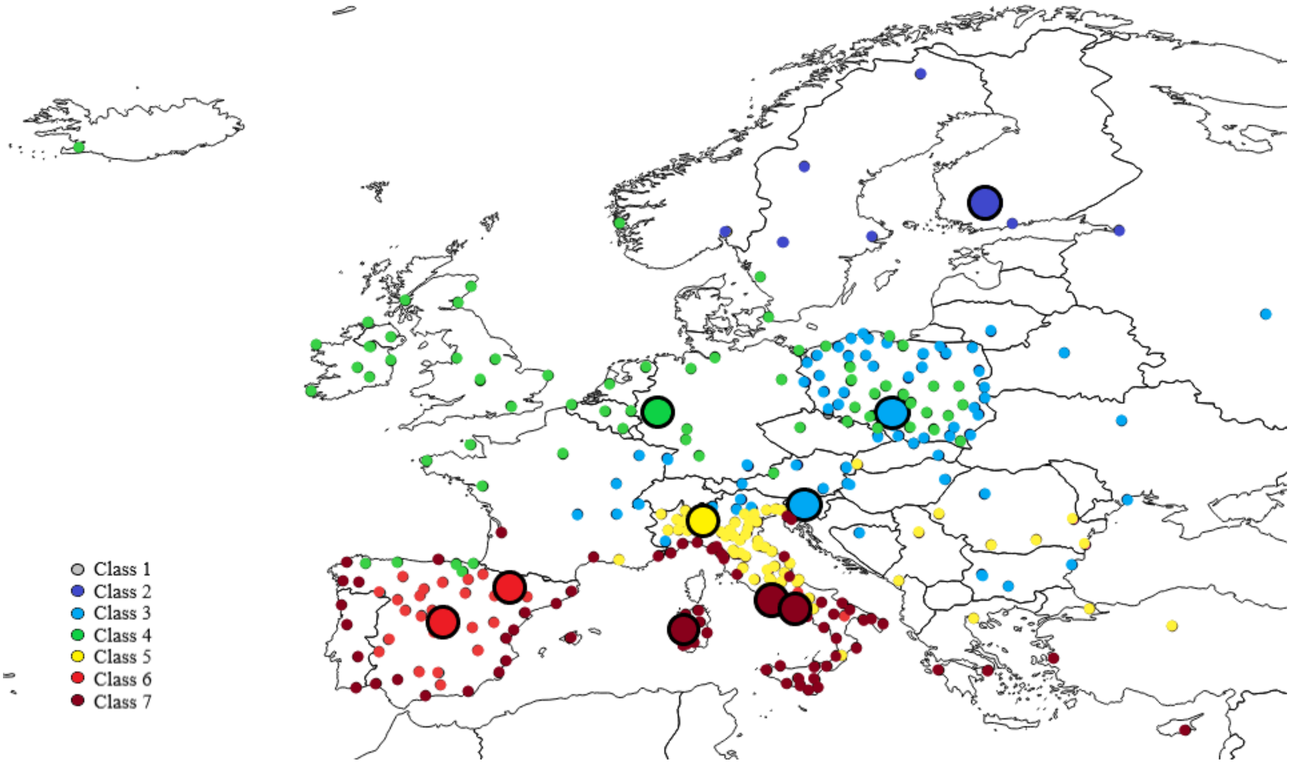

Figure 1: Map of European climates according to the 7 classes identified in Pernigotto et al. (2019). Larger dots indicate the representative climates.

Table 1: Climate classes and representative climates, characterized by means of heating and cooling degree-days calculated according to a base temperature of 18 °C (HDD_{18} and CDD_{18}).

ID	Class	Number of climates	Included regions or climates	Representative climates	Country	HDD_{18} [K d]	CDD_{18} [K d]
1	1	2	Kasprowy Wierch and Sniezka	N/A	N/A	N/A	N/A
2	2	10	Scandinavia and Russia	Tampere	Finland	5020	22
3a	3	68	Eastern Europe, Alpine region, mountain areas in the Balkans	Ljubljana	Slovenia	3383	168
3b				Czestochowa	Poland	3685	103
4	4	67	Western Europe and part of Poland	Koln	Germany	3029	80
5a	5	69	Inland Italy and north of the Balkans	Milan	Italy	2024	671
5b				Lodi		2328	570
5c				Varese		2353	414
6a	6	29	Inland Spain	Madrid	Spain	1965	628
6b				Huesca		2096	433
7a	7	73	Mediterranean and south Europe Atlantic coastal regions	Caserta	Italy	1347	740
7b				Latina		1217	807
7c				Oristano		1285	682

Sample of reference buildings

The selection of a suitable sample of reference buildings plays a major role in building simulation analyses, as it can be seen for instance in the rich literature discussing the BESTEST cases for the validation of building energy simulation codes according to the ANSI/ASHRAE 140. In this work, a dedicated sample of 48 residential reference buildings, developed according to a full factorial plan, was adopted. The sample is not representative of the current European residential building stock and it was generated to show different sensitivities to weather solicitations, specifically for research on weather data for building simulation. As shown for instance in (Pernigotto *et al.*, 2014 and 2020), it accounts for different average insulations of the envelope and various amounts of solar gains admitted into the building, ensuring a variety of ratios between thermal losses and gains, as well as of capabilities to store the cumulated gains.

Except for the windows' area and orientation, each building configuration has the same geometry, i.e., a square floor area of 100 m^2, an internal height of 3 m and the four façades oriented towards the main cardinal directions.

As regards the common features of all buildings:

- Thermal bridges are neglected, and the floor is modelled with a crawl space, without direct thermal contacts with the ground.
- All surfaces of the building envelope are clear (i.e., the surface solar absorptance is 0.3), except for the external side of the roof and the internal side of the floor, which are darker (i.e., the surface solar absorptance is 0.6).
- Surface convective heat transfer coefficients are constant and defined according to the technical standard EN ISO 6946:2017.
- Internal gains are set equal to 4 W m^{-2}, half radiative and half convective, and the ventilation rate is constantly equal to 0.3 ACH (UNI 10339:1995, UNI/TS 11300-1:2014).
- The *HVAC* system is ideal, with heating and cooling setpoints of 20 and 26 °C, respectively. The system is operative for the whole year without specific heating and cooling season schedules.

The rest of the features characterizing opaque and transparent components, including windows' area and orientation, were varied according to a factorial plan with two or three levels for each considered factor:

1. *Thermal inertia of the opaque elements*, characterized by means of two alternative structural massive layers, both with thermal resistance of about 0.8 m^2 K W^{-1}:
   a. Timber components (thickness s = 0.10 m, thermal conductivity λ = 0.13 W m^{-1} K^{-1}, density ρ = 399 kg m^{-3}, specific heat capacity c = 1880 J kg^{-1} K^{-1}),
   b. Concrete components (s = 0.30 m, λ = 0.37 W m^{-1} K^{-1}, ρ = 1190 kg m^{-3}, c = 840 J kg^{-1} K^{-1});
2. *Insulation level of the opaque elements*, expressed by means of the thickness s of an insulation layer of polystyrene (λ = 0.04 W m^{-1} K^{-1}, ρ = 40 kg m^{-3}, c = 1470 J kg^{-1} K^{-1}), applied to the external side of the component:
   a. Low insulation level, with s = 0.05 m and U-value equal to 0.45 W m^{-2} K^{-1},
   b. High insulation level, with s = 0.15 m and U-value equal to 0.21 W m^{-2} K^{-1};
3. *Type of window* (two kinds of double-pane glazing, with the same U-value = 1.1 W m^{-2} K^{-1} but different solar heat gain coefficient *SHGC*, both with a timber frame with U-value = 1.2 W m^{-2} K^{-1}):
   a. Low *SHGC* = 0.35,
   b. High *SHGC* = 0.61;
4. *Windows' area* (two sizes with the frame corresponding to 20 % of the whole area):
   a. Small windows of 14.56 m^2,
   b. Large windows of 29.12 m^2;
5. *Windows' orientation*:
   a. All windows in the east façade,
   b. All windows in the south façade,
   c. All windows in the west façade.

Simulations were run with TRNSYS 18 with hourly timestep. Annual peak loads and annual and monthly energy needs for space heating and cooling were saved as simulation outputs.

Analysis of simulation outputs

The analysis of simulation outputs was performed for the sample as a whole. First, a descriptive representation of the distribution of annual energy needs and peak loads and monthly energy needs was generated for each representative climate, with the aim to identify potential overlapping on the results. Furthermore, the fraction of buildings in the sample with needs larger than 1 kWh m^{-2} was calculated at both annual and monthly basis. Finally, the sets of annual heating and cooling energy needs and peak loads were tested for the 12 representative climates by means of the non-parametric Kolmogorov-Smirnov statistical test, performed to identify cases of equality of the result distributions according to a statistical significance of 5 %, with the aim to verify the considerations from the descriptive analysis.

Results

Annual peak loads and energy needs

Figures 2 depicts the distribution of annual peak loads and energy needs for space heating and cooling for the whole sample of buildings and in each representative climate.

Annual peak loads for space heating range from 0.5 to almost 8 kW, depending on the considered climate and on the thermal quality of the building envelope. As it can be observed, each representative climate can be characterized by its own distribution of peak loads, without marked overlapping. As expected, this is not true for those representative climates belonging to the same climate class, as is for example for the two light blue functions drawn for Ljubljana (*3a*) and Czestochowa (*3b*) or the light red ones for Madrid (*5a*) and Huesca (*5b*).

Furthermore, the warmer the climate class, the lower the differences among its representative climates. Similar trends are confirmed for annual energy needs for space heating, ranging respectively from 74 to 190 kWh m^{-2} a^{-1} (in *2*), 40 to 135 kWh m^{-2} a^{-1} (in *3a* and *3b*), 28 to 106 kWh m^{-2} a^{-1} (in *4*), 12 to 82 kWh m^{-2} a^{-1} (in *5a*, *5b* and *5c*), 2 to 70 kWh m^{-2} a^{-1} (in *6a* and *6b*), and 0 to 44 kWh m^{-2} a^{-1} (in *7a*, *7b* and *7c*). Just 1 building in *7a* and *7b* (Caserta and Latina) has annual heating needs lower than 1 kWh m^{-2} a^{-1}.

Annual peak loads for space cooling show values between 0 and 9.5 kW, but with trends very different from those observed for space heating. Indeed, a significant degree of overlapping can be detected, in particular among representative climates *2*, *3a*, *3b* and *4*, and *5a*, *5b*, *5c*, *6a*, *6b*, *7a*, *7b* and *7c*. Focusing on the largest peaks (i.e., larger than 5 kW), the different curves are completely overlapped and some colder localities show peak loads even larger than some warmer ones. Overlapping is present also in annual energy needs for space cooling, although more limited. Cooling needs range from 0 to 51 kWh m^{-2} a^{-1} (in *2* and *4*), 0 to 64 kWh m^{-2} a^{-1} (in *3a* and *3b*), 7 to 66 kWh m^{-2} a^{-1} (in *5a*, *5b* and *5c*), 7 to 111 kWh m^{-2} a^{-1} (in *6a* and *6b*), and 14 to 136 kWh m^{-2} a^{-1} (in *7a*, *7b* and *7c*). 5, 9 and 19 buildings have null annual needs, respectively in climates *3b* (Czestochowa), *4* (Koln) and *2* (Tampere). Analysing the results, two groups can be distinguished: the colder climates (*2*, *3a*, *3b* and *4*) and the warmer ones (*5a*, *5b*, *5c*, *6a*, *6b*, *7a*, *7b* and *7c*), with representative climates in class *5* distinct from the others just for the quartile of the sample of buildings characterized by the largest cooling needs.

Monthly energy needs

Analysing the sample of all monthly needs and building configurations, the fraction of months with at least 1 kWh m^{-2} m^{-1} of heating demand goes from about 35 % in *7b* (Latina) to about 75 % in *2* (Tampere). As far as the cooling needs are concerned, the fraction of months with at least 1 kWh m^{-2} m^{-1} of cooling demand ranges from 15 % in *2* (Tampere) to 55 % in *7b* (Latina). As it can be noticed in Figure 3, fractions are similar for representative climates in the same class and different in case of an inter-class comparison. An exception to this are Ljubljana (*3a*), Czestochowa (*3b*) and Koln (*4*), whose fractions are almost the same. As regards cooling needs, again two groups can be identified: one with fractions ranging from 15 % to 25 % (*2*, *3a*, *3b* and *4*) and another from 40 % to 55 % (*5a*, *5b*, *5c*, *6a*, *6b*, *7a*, *7b* and *7c*).

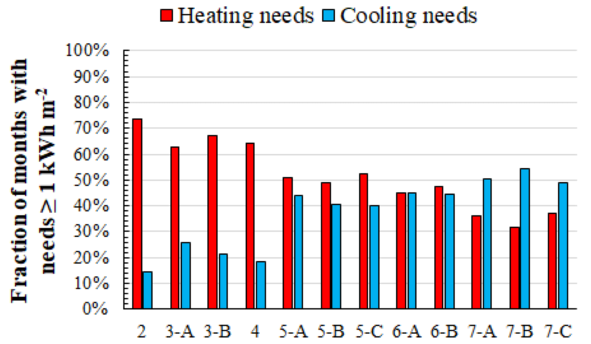

Figure 3: Fractions of months with at least 1 kWh m^{-2} m^{-1} of energy needs in the whole sample.

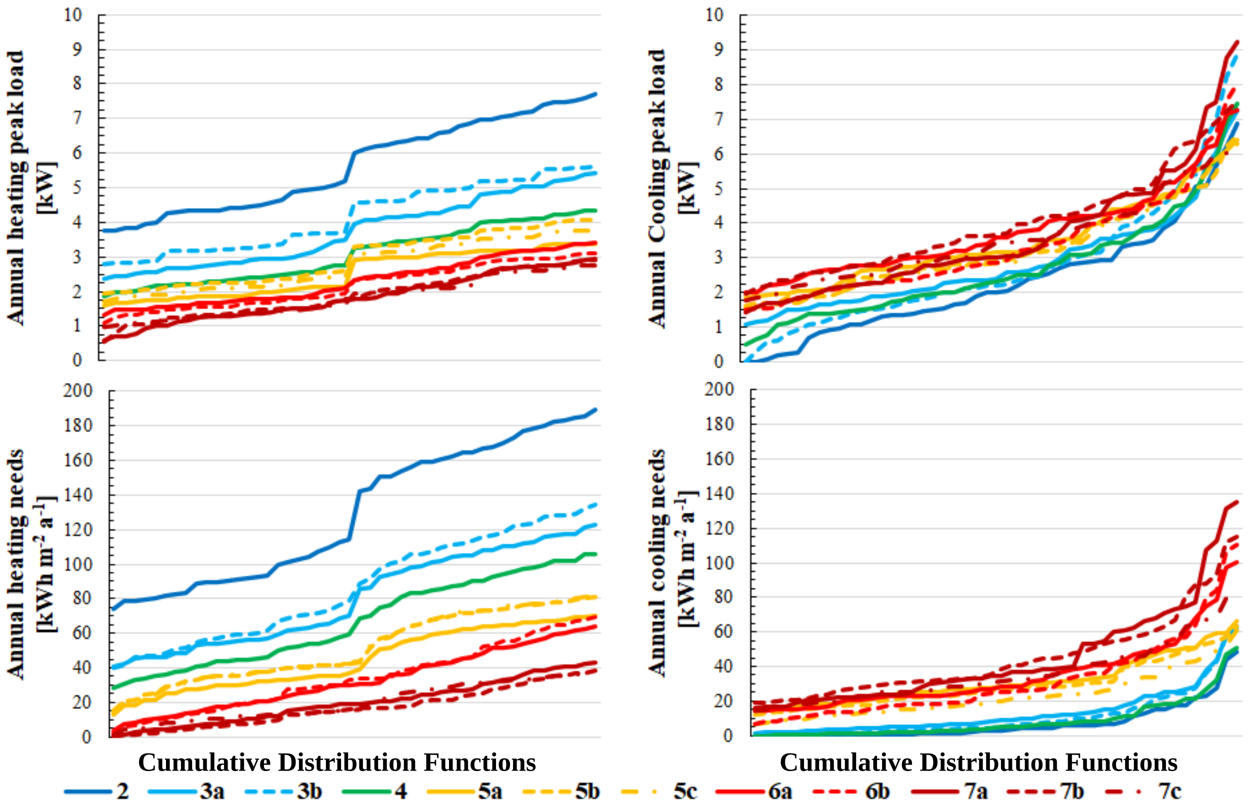

Figure 2: Distributions of heating (left) and cooling (right) annual peak loads (top) and annual energy needs (bottom) for the representative climates.

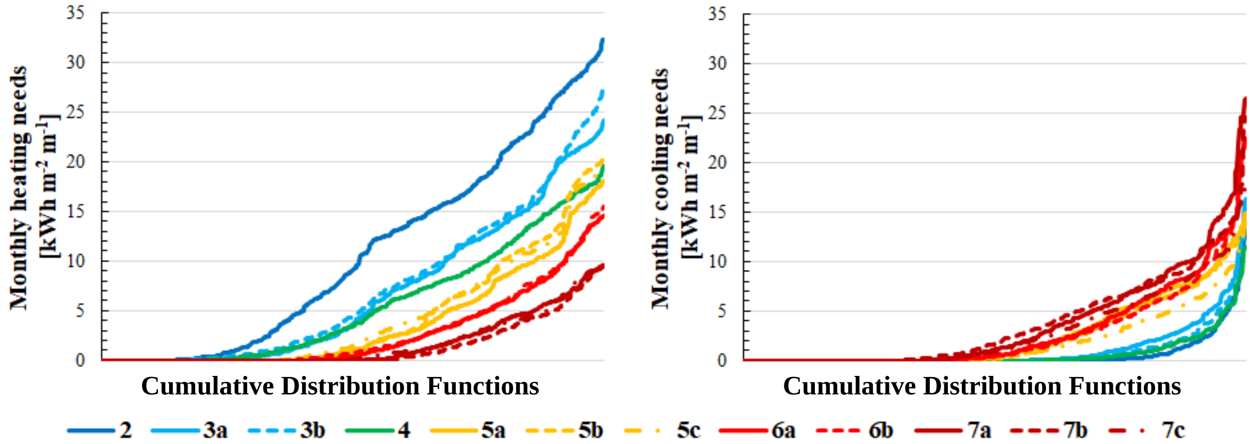

Figure 4: Distribution of heating (left) and cooling (right) monthly energy needs for the whole sample and each representative climate.

Figure 4 shows the distribution of monthly energy needs for space heating and cooling for the whole sample of buildings and each representative climate. The shorter time-discretization of the results confirms what seen in the previous section with an annual basis:

- For space heating needs, representative climates belonging to the same climate class present very similar trends while the inter-class comparisons reveal distinct trends without overlapping;
- For space cooling needs, the curves are clustered into two groups, with European northern cold climates separated from the southern warm ones.

In Figures 5 and 6, the distributions of monthly energy needs are reported for selected months of the year. Specifically, Figure 5 depicts the heating needs distributions for the months from October to March and Figure 6 the cooling ones from April to September. It can be commented that the general trends observed in previous charts are kept, although some differences are detectable among the months. As regards the heating needs, some degree of overlapping among the representative localities can be seen at the beginning or at the end of the heating season, especially among the warmest climates. For example, in March, the needs of representative climates *3a*, *3b* and *4* are very close each other and the same can be said for climates belonging to classes *5*, *6* and *7*. Furthermore, the results for climate *4* are partially overlapped to those for *5a*, *5b*, *5c* in December and January. Focusing on the cooling needs, the results of the representative climates look more distinct at the beginning and at the end of the cooling season, which can be observed to impact with different magnitude in the various climate zones. On the contrary, the hottest months of the year, i.e., June, July and August, are in good agreement with the trends noticed for the global distributions of Figure 4.

Statistical analysis

Each set of 48 annual energy needs and peak loads, for both space heating and cooling, underwent to Kolmogorov-Smirnov statistical tests, assuming a statistical significance level of 5 %. Each set of results was compared with all other simulated sets. A statistically significant *p*-value (*p*-value < 0.05, grey cells in Table 2) indicates that the compared sets of data are different while the opposite can be concluded when it is non-significant (*p*-value ≥ 0.05, yellow cells in Table 2). For sake of clarity, Table 2 highlights with red colour also those tests which "failed", i.e., tests between sets of results from representative climates belonging to different climate classes which were found non-statistically significant (i.e., not different), and tests between sets of results from representative climates belonging to the same climate class which proved to be statistically significant (i.e., different).

Starting from the annual heating needs, it can be seen that all tests between sets of results obtained from representative climates belonging to different classes are significant (i.e., their distributions are different), while tests for climates belonging to the same class generally resulted as non-significant (i.e., the distributions belong to the same population). The only exception is for *5a* with respect to *5b* and *5c*: Milan (*5a*) resulted different from the two other representative climates of its class but it was not fount similar to any other representative climate. As regards the annual cooling needs, findings are very different. As a general comment, the results of the first 4 representative climates are always different from the last 8 ones. On the contrary, inter-class tests within these two groups gave non-statistically significant *p*-values in several occurrences, meaning that the distributions of cooling needs for the reference sample are not different. All tests among sets of needs calculated from simulations with representative climates belonging to the same class are non-significant, except for *5a* with respect to *5c*. The tests of peak loads show a larger number of non-significant results, for both heating and cooling. As regards heating, this is found in particular for comparisons between *4* and *5a* / *5b*, *6a* and *7a* / *7b*; focusing on the inter-class comparisons, instead, statistically significant *p*-values are seen between *3a* and *3b* and between *5a* and *5b*. In the case of the cooling peak loads, the large majority of *p*-values is non-significant. Besides the general trend observed for the annual cooling needs, some non-significant differences are detected also between *3a* and *5c* / *6b* / *7a*.

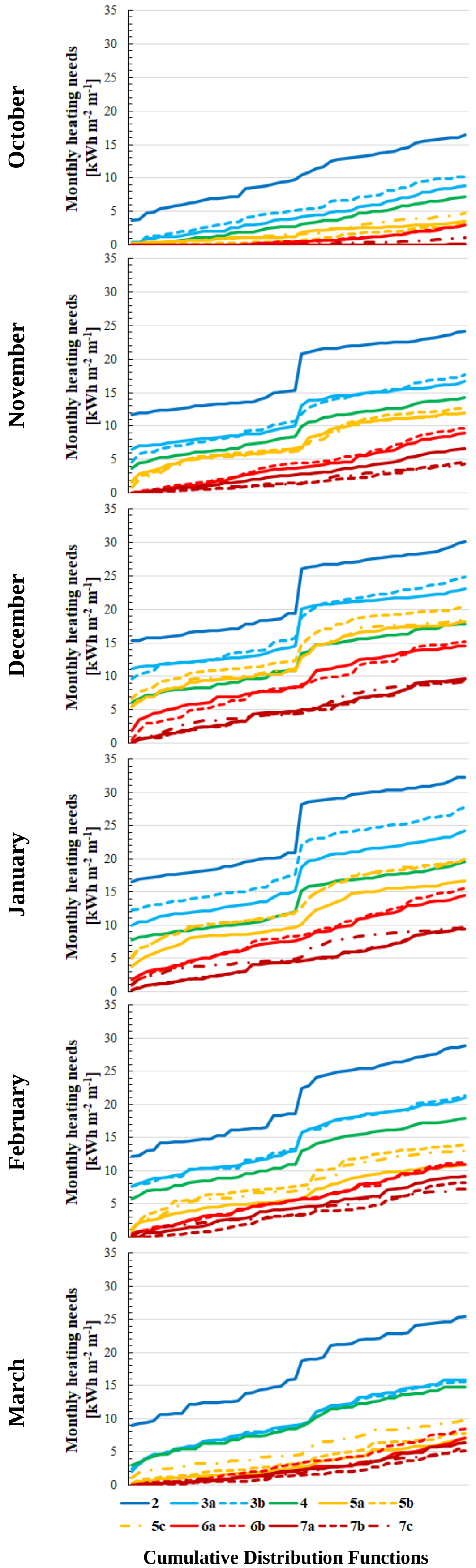

Figure 5: Distributions of heating monthly needs for the whole sample and each representative climate in the coldest months of the year.

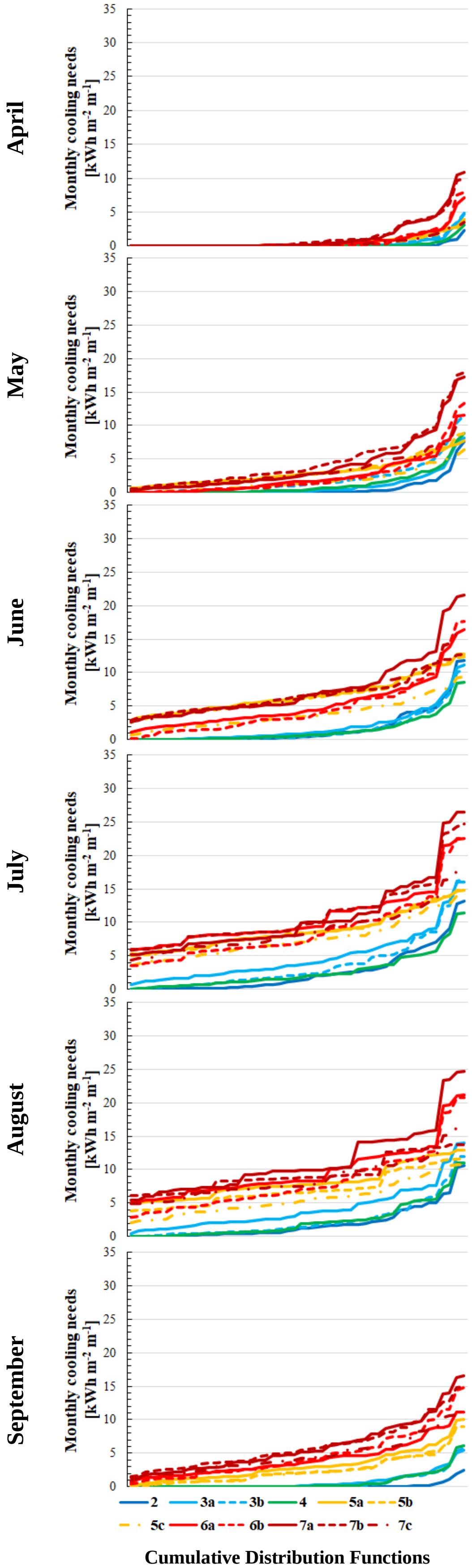

Figure 6: Distributions of cooling monthly needs for the whole sample and each representative climate in the hottest months of the year.

Table 2: p-values of Kolmogorov-Smirnov tests for annual heating and cooling needs and peak loads. In grey those cells with significant p-value, in yellow those with non-significant p-value. In bold red those comparison with either significant p-value in same-class comparison or non-significant p-value with inter-class comparisons.

Annual heating needs

	2	3a	3b	4	5a	5b	5c	6a	6b	7a	7b	7c
2		< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
3a			0.48	0.05	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
3b				< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
4					< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
5a						**0.03**	**0.01**	0.03	0.05	< 0.01	< 0.01	< 0.01
5b							1.00	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
5c								< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
6a									0.95	0.01	< 0.01	< 0.01
6b										< 0.01	< 0.01	< 0.01
7a											0.48	0.65
7b												0.22
7c												

Annual cooling needs

	2	3a	3b	4	5a	5b	5c	6a	6b	7a	7b	7c
2		< 0.01	**0.08**	**0.22**	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
3a			0.08	0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
3b				**0.82**	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
4					< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
5a						0.48	**0.01**	**0.65**	**0.14**	0.05	0.01	**0.48**
5b							0.05	**0.48**	**0.33**	< 0.01	< 0.01	**0.14**
5c								0.01	**0.14**	< 0.01	< 0.01	< 0.01
6a									0.05	**0.22**	0.01	**0.33**
6b										< 0.01	< 0.01	0.03
7a											0.48	0.38
7b												0.22
7c												

Annual heating peak loads

	2	3a	3b	4	5a	5b	5c	6a	6b	7a	7b	7c
2		< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
3a			**0.01**	0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
3b				< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
4					< 0.01	**0.48**	**0.08**	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
5a						**<0.01**	0.08	0.05	< 0.01	< 0.01	< 0.01	< 0.01
5b							0.14	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
5c								< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
6a									0.33	0.01	0.01	< 0.01
6b										**0.08**	**0.08**	0.03
7a											0.99	0.65
7b												0.82
7c												

Annual cooling peak loads

	2	3a	3b	4	5a	5b	5c	6a	6b	7a	7b	7c
2		0.01	**0.65**	**0.22**	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
3a			0.48	**0.65**	0.01	0.03	**0.14**	< 0.01	**0.22**	**0.08**	< 0.01	< 0.01
3b				**0.99**	< 0.01	0.01	0.01	< 0.01	0.03	0.01	< 0.01	< 0.01
4					< 0.01	0.01	0.05	< 0.01	0.03	0.03	< 0.01	< 0.01
5a						0.48	0.33	**0.48**	**0.22**	**0.82**	**0.08**	**0.95**
5b							0.95	**0.14**	**0.82**	**0.82**	0.05	**0.48**
5c								**0.08**	**0.99**	**0.82**	0.05	**0.22**
6a									0.05	**0.22**	**0.95**	**0.65**
6b										**0.82**	0.03	**0.33**
7a											0.14	0.65
7b												0.33
7c												

Discussion and Conclusion

In this research we analysed by means of building energy simulation a methodology for weather-based climate clustering and representative climate identification presented by the authors in previous research. For a group of 12 climates representative of 6 classes and 318 European climates, TRNSYS simulations were run for a sample of 48 reference buildings. Simulated annual peak loads and annual and monthly needs for space heating and cooling were analysed according to descriptive and non-parametric statistical techniques, with the aim of identifying potential overlapping between the results obtained from climates representative of different classes or inhomogeneity from climates representative of the same class. As a general goal, this research discussed the applicability of the proposed weather-based climate clustering to building energy simulation analysis aimed at generating findings for the development of energy strategies at European level. We found that:

- The distributions of the annual peak loads for the sample of reference buildings are very different considering either heating or cooling. While for heating each representative climate gives specific and distinct results, the same is not true for cooling peak loads, for which it is possible to identify common trends characterizing two clusters of climates (colder and warmer ones).
- The distributions of annual heating needs show that the adoption of the proposed set of representative climates can be effective to have an overall characterization of the building energy performance for space heating at European scale. The same is generally confirmed also analysing simulation outputs on a shorter time-discretization (i.e., the month), although with a larger degree of overlapping among the results of some climate classes at the beginning and the end of the heating season.
- Finally, the analysis of annual and monthly cooling needs confirmed the presence of two main groups of climates giving similar building performances, which can be exploited to reduce the calculation effort when the goal is to characterize only the building energy performance for space cooling at European scale.

As a whole, the proposed weather-based clustering can be considered a "general purpose" climate classification, which can be applied to multiple contexts related to building simulation. While it proved to be suitable when heating demand is concerned, the presence of redundant results makes the computational effort suboptimal in case of the evaluation of cooling demand. Consequently, if the aim of a researcher or a policy maker is to assess only the energy performance for cooling at European scale, simplifications can be applied. On the contrary, when the focus is put on heating or global energy demand, the adoption of the representative climates obtained through the proposed methodology can be considered satisfactory.

In consideration of these findings, further developments of this research will expand the scope of the analysis and embrace also non-energy performance aspects, such as indoor environmental quality, in order to discuss the efficacy of proposed approach also from an additional perspective.

Acknowledgement

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