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WILL CITIES SURVIVE?

Adequacy of Weather Data Standards to Assess Building Passive Performance During Summer An Application to French Buildings

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ABSTRACT: The energy, environmental and social cost of the spread of HVAC systems in housing in France calls to investigate the impact of climate change on buildings' cooling energy needs. From the Energy Performance Observatory database of buildings, annual cooling energy needs are calculated with the thermal model of the French regulation, COMETH. For these simulations, nine different climate projections from 1981 to 2058 are used with the RCP8.5 scenario, as well as representative years (reference and extreme), constructed from these projections. The cooling needs of a large number of buildings increase from very low values in the past to non-negligible needs in the future. The study of mean and standard deviation of the needs explains this evolution according to two phenomena: an increase in average needs (Phen1), and a repetition and/or intensification of the extreme years (Phen2). Classification by the k-average algorithm shows that we can use representative years to identify vulnerable buildings. This classification brings out differentiated buildings groups along 2 axes: passive and active buildings (Phen1) which can independently be adapted or not to future extremes years (Phen2). In particular, some buildings require special attention, as they are passive on average, but sensitive to future extreme years.

KEYWORDS: Cooling needs, Climate projections, Representative years, Classification.

1. INTRODUCTION

Due to climate change and heatwaves (Riberon et al., 2006), an increase of residential use of air conditioners from 5% in 2005 to 13% in 2016 (Rolland, 2018) was observed in France. This trend was confirmed recently for the entire air-conditioners market since sales increased from 400 000 in 2015 to 823 000 units in 2020 (CODA Stratégies, 2021).

The spread of air conditioning systems would increase electricity demand, greenhouse gas emissions and external temperature resulting from its thermodynamic cycle (de Munck et al., 2013). To limit this spread, the French Thermal Regulation for buildings (RT2012) promotes passive design strategies (the architecture and the building envelope characteristics). Indeed, it requires not exceeding an energy need threshold for comfort and lighting (Videau et al., 2013). The different combinations in passive strategies can be evaluated using a Building

Performance Simulation (BPS) to calculate, for instance, cooling needs.

However, past climate observations are still used in the regulation's BPS. Climate change and future projections are therefore not taken into account even though they may have an impact on the spread of cooling systems. This should lead to reconsider the current standards used to define weather data for BPS. As a result, this paper focuses on the relationship between external future climate conditions and building thermal responses, in the context of thermal regulation and standards.

It aims to (1) evaluate the impact of climate change on building cooling needs, (2) assess the relevance of using representative future climate files to classify buildings in term of cooling needs, and (3) identify those at risk, where the installation of an air conditioner could or will be necessary.

2. METHODOLOGY

This paper follows a four-step method: (i) a selection of 77 collective buildings from the Energy Performance Observatory (OPE) database, (ii) a construction of different climate data files based on future projections and past observations, (iii) a calculation of cooling needs using BPS, and (iv) an analysis of the thermal responses under different climate models and a classification regarding cooling needs for the 77 buildings.

2.1. Building selection

Since RT2012, the characteristics of new buildings, built after 2014, and their associated results are stored in the OPE database (Directorate-General for Energy, 2018). From this database, we selected 77 projects. The selection criteria were: (a) the project contains a single building, (b) the building has at least one collective housing area, and (c) the collective housing must have a cooling need.

2.2. Climate conditions

Three types of climate data are used in this paper, from Paris Montsouris location: (a) past and future times series (both are predicted), (b) reference representative years, and (c) extreme representative years.

(a) For the construction of the predicted past and future climate data, we used 9 climate projections between 1981 and 2019 from the EURO-CORDEX database (Moss et al., 2010). These projections are combinations of Global Climate Models (GCMs) and Regional Climate Models (RCMs) that we consider equiprobable as shown in Table 1. For each of them, only the Representative Concentration Pathway (RCP) 8.5 is considered (Gobiet & Jacob, 2011), which is the most pessimistic gas emission scenario also considered as "business as usual". Beforehand, a bias-correction procedure (Kraiem et al., 2020) was used by employing ERA5 observed data over the same period (1981-2019), followed by a Hermite cubic interpolation from 3 hours to 1 hour.

Table 1: 9 combined climate models with scenario RCP 8.5

N°	Global Climate Model (GCM)	Regional Climate Model (RCM)
1	CNRM-CERFACS-CNRM-CM5	CNRM-ALADIN 63
2	CNRM-CERFACS-CNRM-CM5	SMHI-RCA 4
3	ICHEC-EC-EARTH	SMHI-RCA 4
4	ICHEC-EC-EARTH	SMHI-RCA 4
5	ICHEC-EC-EARTH	SMHI-RCA 4
6	MOHC-HadGEM2-ES	CNRM-ALADIN 63
7	MOHC-HadGEM2-ES	ICTP-RegCM4-6
8	MOHC-HadGEM2-ES	MOHC-HasREM3-GA7-05
9	MPI-M-MPI-ESM-LR	ICTP-RegCM4-6

(b) The ISO 15927-4 provides a method for creating a year of climate data, representing a period of several years, to assess the average annual energy needs for heating and cooling (ISO, 2005). Using at least 30 years enables to overcome the internal variability of climate (Maher et al., 2020). Thus, from the predicted data, over the periods (1981-2019) and (2020-2058), two reference years were created for the past and future periods, respectively.

(c) Also from the predicted data, past (1981-2019) and future (2020-2058) extreme years are constructed using a method strongly inspired by the Netherlands standard (NEN, 2020) based on parts 2, 4 and 5 of the same ISO 15927 standard (ISO, 2005).

As a result, we have 78 predicted years (1981-2058), two reference years and two extreme years of climate data for the past and future. Combined with 77 buildings and 9 models, this represents more than 56 000 simulations as shown in Table 2.

Table 2: Summary of simulations

Period	Climate	Years	Models	Buildings	Total
Past	Predicted	39	9	77	27 027
	Reference and extreme	2			1 386
Future	Predicted	39			27 027
	Reference and extreme	2			1 386
					56 826

2.3. Building Performance Simulations

The 56 826 BPS were performed using COMETH, which is the thermal model used in the French building thermal regulation RT2012. It relies on a 5R1C thermal network model. Such model has proven to be efficient at estimating cumulative indicators such as heating and cooling energy needs (da Silva et al., 2016). The simulation calculates the "bioclimatic" need. This is the consumption of an ideal energy system, with an efficiency of one, and systematically reaching the set temperature. This measure allows ignoring the active energy systems and measures the actual passive performance of the building. Furthermore, in the context of the regulation of buildings energy performance, the internal loads and ventilation, limited to the hygiene flow rate, are conventionally established.

2.4. Analysis and classification

Our analysis includes 3 steps.

First, we assess the impact of climate change on buildings by observing, between the past (1981-2019) and the future (2020-2058), the average cooling needs and the related Standard Deviation (SD), defined as follows for the past:

$$\bar{N}_{past} = \frac{1}{39} \sum_{i=1981}^{2019} N_i \quad (1)$$

$$\Delta N_{past} = \sqrt{\frac{1}{39} \sum_{i=1981}^{2019} (N_i - \bar{N}_{past})^2} \quad (2)$$

where N_i are the annual cooling needs for year i , \bar{N}_{past} is their past mean, ΔN_{past} is their past SD.

Second, we compute for a given model, two distributions (39 past and 39 future annual cooling needs) for 77 buildings to understand their evolution.

Third, we perform two parallel classifications of the 77 buildings with the k-means algorithm. The first clustering is based on the Euclidean distance from one building to another in a 27-dimensional space consisting of the following variables (past, future average needs and future SD for the 9 models):

$$\{\bar{N}_{past}^1, \bar{N}_{futu}^1, \Delta N_{futu}^1, \dots, \bar{N}_{past}^9, \bar{N}_{futu}^9, \Delta N_{futu}^9\}$$

Similarly, the second clustering takes into account 27 alternative variables based on the past, future reference years and extreme future year for the 9 models:

$$\{N_{ref,past}^1, N_{ref,futu}^1, N_{ext,futu}^1, \dots, N_{ref,past}^9, N_{ref,futu}^9, N_{ext,futu}^9\}$$

Finally, we display the different clusters on graphs in two dimensions, being projections of the 27 dimensions space. This helps to observe the distinction between groups according to different variables.

3. RESULTS AND DISCUSSION

The results are detailed by following the 3-point analysis approach presented in section 2.4.

3.1. Two climate change impact phenomena

Fig. 1 shows, for each building and for each model, the average future cooling needs as a function of the average past cooling needs. For each model, we observe a linear pattern. All the linear regressions are above the $y=x$ curve, which corresponds to an increase in cooling needs. This increase varies according to the models with slopes ranging from 1.1 to 2. We thus have a first phenomenon (Phen1) of proportional increase in needs: *a shift effect of the needs on average*.

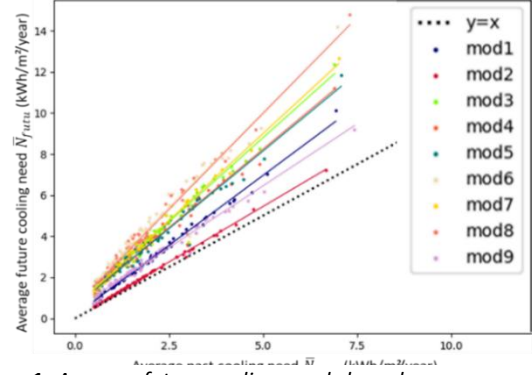


Figure 1: Average future cooling needs based on average past cooling needs for the 77 buildings and 9 models.

A similar linear behaviour is observed in Fig. 2 which represents, for each building and for each model, the future cooling needs SD as a function of the past cooling needs SD. All the points are above the $y=x$ curve, which corresponds to an increase of the SD (the slopes are ranging from 1.2 to 1.8). In particular, this leads to more intense and/or more frequent extreme needs. This is the second phenomenon (Phen2): *the stretching of the SD*.

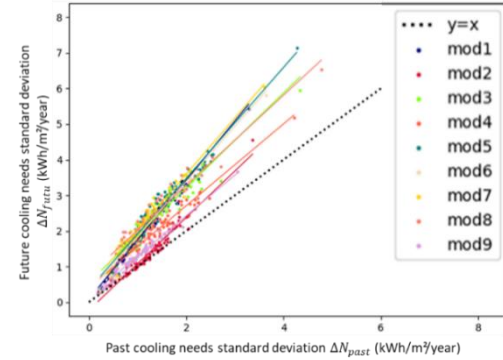


Figure 2: Future cooling needs SD based on past cooling needs SD for the 77 buildings and all models.

The linear trends could be due to the homogeneity of the selected buildings (same type of use, the same air exchange rate, and RT2012 compliant buildings).

3.2. Distribution in past and future cooling needs

Fig. 3 shows the past (blue) and future (red) cooling needs distributions, for the 77 buildings and model 6. On the left side of the distributions (low needs), we note that the number of past annual cooling needs is higher than the future. Conversely, on the right side (needs above an arbitrary threshold); the number of future annual cooling needs is greater than the past. Thus, a large number of individuals has exceeded the arbitrary threshold between past and future. This migration may be due to the increment in

mean (Phen1) or the repetition and/or intensification of extreme years (Phen2).

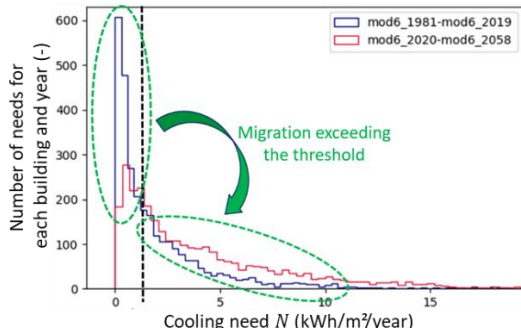


Figure 3: Distributions of past (1981-2019) and future (2020-2058) cooling needs for model 6

More than the increase in consumption, the crossing of the threshold and the creation of a need, whether it is on average (Phen1) or punctual (Phen2) are the real issue. Indeed, the transition from a nearly-zero cooling need to a significant cooling need could potentially require the installation of an air conditioner.

We observe that other models give similar distributions in shape (thanks to the bias correction of the models over the past period and the linearity observed for all the models Fig. 1 and 2) but not in quantitative value (since the slopes are different for each model). The question is to distinguish passive buildings from those vulnerable to climate change. Taking into account the health risks associated with heat waves, the latter will potentially require the installation of an air conditioner. Thus, the priority is to identify the different groups of buildings according to their sensibility to climate change.

3.3. Classification and identification

This section is divided in three sections. The first one shows the comparison between two building classifications and the other two sections illustrate the clusters in a bi-dimensional space.

Two classifications comparison

Table 3 compares the clusters of 77 buildings (column 1) that are made by the two k-means classifications: on the one hand, with the 27 mean and SD variables (cluster name in column 2), and on the other hand with the 27 reference and extreme variables (cluster name in column 3). Each colour represents a cluster. There are nine clusters for each of the two classifications. Without going into technical details, the choice of nine clusters was made by studying the percentages of variations obtained by a Principal Component Analysis (PCA) (Yang, 2019).

Table 3: Comparison of the two clustering (each line is a building, with its corresponding cluster colours for the first and second classifications)

Building	1st clustering	2nd clustering	Building	1st clustering	2nd clustering	Building	1st clustering	2nd clustering
19 zone_1	0	3	11 zone_1	3	0	30 zone_1	5	5
30 zone_1	0	3	18 zone_1	3	0	35 zone_1	5	5
20 zone_2	0	3	23 zone_2	3	0	26 zone_1	5	5
29 zone_2	0	3	30 zone_1	3	0	33 zone_1	5	5
22 zone_2	0	3	46 zone_1	3	0	40 zone_1	5	5
43 zone_18	0	3	67 zone_2	3	0	52 zone_1	5	5
51 zone_1	0	3	8 zone_3	3	4	50 zone_3	5	5
51 zone_2	0	3	8 zone_1	3	4	76 zone_1	5	5
54 zone_1	0	3	8 zone_1	3	4	5 zone_1	4	2
54 zone_2	0	3	17 zone_1	3	4	17 zone_2	4	2
1 zone_1	7	3	25 zone_1	3	4	49 zone_2	4	2
29 zone_1	7	1	48 zone_1	3	4	50 zone_2	4	2
32 zone_1	7	1	60 zone_1	3	4	70 zone_2	4	2
70 zone_1	7	1	66 zone_2	3	4	71 zone_1	4	2
25 zone_1	7	1	69 zone_1	3	4	19 zone_2	6	8
2 zone_1	1	7	74 zone_1	3	4	23 zone_1	6	8
3 zone_2	1	7	37 zone_2	8	4	61 zone_1	6	8
18 zone_3	1	7	7 zone_2	8	6	58 zone_1	2	8
21 zone_4	1	7	9 zone_1	8	6	58 zone_2	2	8
28 zone_1	1	7	23 zone_2	8	6			
36 zone_1	1	7	37 zone_1	8	6			
44 zone_1	1	7	46 zone_1	8	6			
53 zone_1	1	7	50 zone_1	8	6			
53 zone_1	1	7	77 zone_1	8	6			

We observe that the 2 classifications give very similar results. Only 2 buildings are not classified in the same cluster from one classification to the other ("1.zone_1" and "37.zone_2"). Moreover, the cluster n°3 (1st clustering) is divided into 2 clusters (n°0 and n°4, 2nd clustering). In return, clusters n°6 and n°2 (1st clustering) are combined into a single cluster (n°8, 2nd clustering).

The representative climate files (2nd clustering) lead to an equivalent clustering while requiring much less computation than the first one. Indeed, we recall that the use of reference years allows to divide by 20 the number of simulations performed and presented in Table 2.

First group distinction (Phen1)

Fig. 4 and 5 represent future reference cooling needs as a function of past reference cooling needs for each building, coloured according to its clusters, and for models 4 and 7, respectively. These are two bi-dimensional projections of the 27-dimensional space in which the classification was done.

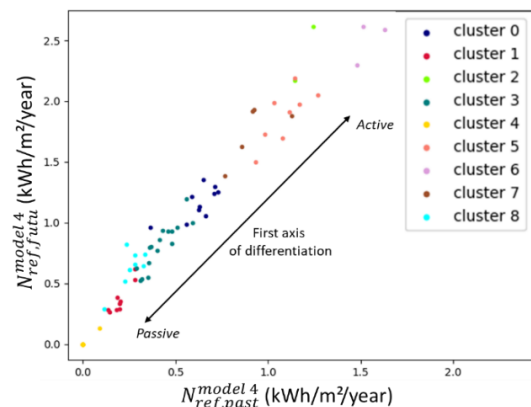


Figure 4: Future reference as a function of past reference cooling needs for model 4

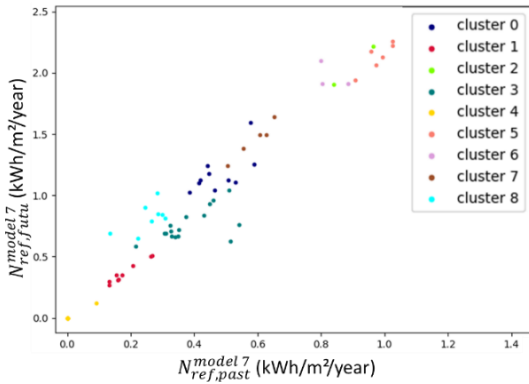


Figure 5: Future reference as a function of past reference cooling needs for model 7

CLUSTER DIFFERENTIATION AXIS: We first observe a linear behaviour of the future and past reference years as in Fig. 1. We thus observe a first distinction between the different clusters on this linear axis. On the one hand, the passive buildings (bottom left) have low cooling needs in the past and in the future. On the other hand, the active buildings (top right) have high cooling needs in the past and in the future. This is a first axis of differentiation of the clusters.

PHENOMENON 1 (PHEN1): The increase of the average needs has the effect of transforming the buildings, initially passive, into active buildings in the future: this is notably the case of the clusters in the center (n°0 blue and n°7 brown). These groups are vulnerable to climate change for Phen1. Belonging to these groups may lead to a long-term purchase of an air conditioner, but all the models should be used for a quantitative approach.

We observe that the groups, on the bottom left, which are passive on average have different colours (n°1 red, n°3 teal and n°8 cyan) while their points are close to each other. Why would the k-means algorithm distinguish them? The answer can be seen in a second projection.

Second group distinction (Phen2)

Fig. 6 and 7 show the future extreme cooling needs as a function of past reference needs for each building, coloured according to its clusters, and for models 4 and 7, respectively. As before, these are 2 two-dimensional projections of the space in dimension 27.

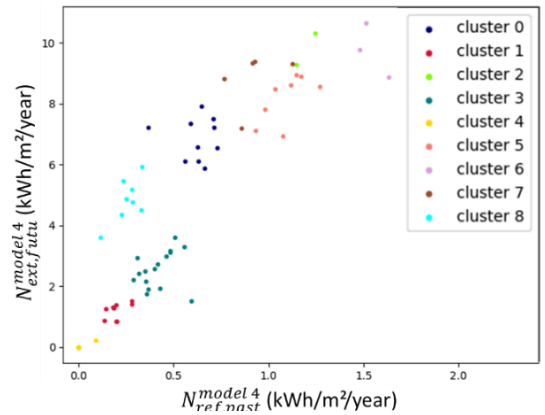


Figure 6: Extreme future as a function of past reference cooling needs for model 4

CLUSTER DIFFERENTIATION AXIS: We observe, contrary to the linear behaviour of the previous figures, a stretching of the clusters on the future extreme values. Indeed, for groups having similar average needs (aligned on the same vertical axis), they differentiate on their extreme cooling needs: for instance, cluster n°3 (teal) and n°8 (cyan). This is therefore a second axis of distinction of clusters. At the bottom, clusters are adapted to the extreme future. In contrast, at the top, clusters are not adapted to the extreme future. In summary, Fig. 7 shows the two axis of differentiation.

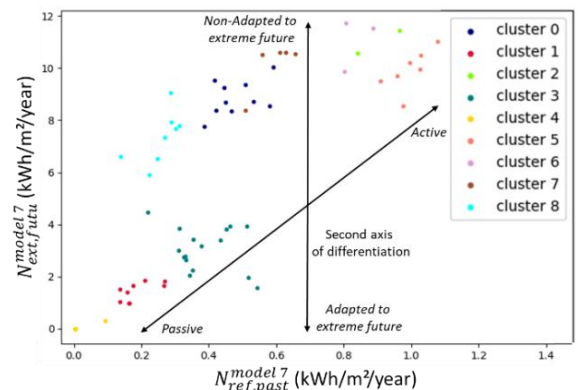


Figure 7: Extreme future as a function of past reference cooling needs for model 7

PHENOMENON 2 (PHEN2): The vulnerability of buildings not adapted to future extremes is at the origin of a punctual creation of cooling need and/or represents a health risk. For example, if we had considered only past – future reference cooling needs, cluster n°8 (cyan) would not have been differentiated from cluster n°3 (teal). However, we observe that the cooling needs of future extreme years are much more significant than the reference years. Belonging to cluster n°8 therefore leads to a

health risk and/or the possibility of purchasing an air conditioner immoderately (Phen2). Concerning the impact of extreme climates in the purchase of an air conditioner, it would be interesting to study the probability of occurrence of these types of climates. Whatever the model chosen, the buildings' clusters can be classified using 2-differentiation axis:

- Clusters 1, 3 and 4 like passive and adapted.
- Cluster 8 like passive not adapted (Phen2).
- Clusters 0 and 7 from passive to active (Phen1).
- Clusters 2, 5 and 6 like active.

The description of the buildings physical characteristics did not reveal any clear building parameter that would differentiate them a priori, despite the approach limited to cooling needs. In addition, the great homogeneity of the buildings can also explain this result. Walls insulation may be the discriminating parameter as the temperature increase is the main effect of climate change. However, in summer in France, its impact is difficult to quantify a priori because:

- it is of 2^{sd} order in the well-insulated buildings studied with an air change rate limited to the hygiene flow rate,
- its thermal effects are antagonists, limiting heat transfer during the day and confining heat indoors at night.

4. CONCLUSIONS AND PERSPECTIVES

(1) The study evaluates, on a large sample of buildings, the impact of climate change according to two dimensions: an increase in the average and an increase in the internal variability of the climate (SD and extreme). These two effects induce the migration from low past cooling needs to non-negligible future cooling needs that may require the purchase of an air conditioner.

(2) The study has shown the relevance of using representative years (reference and extreme) to classify buildings in accordance with their cooling needs. The approach developed showed that it was possible, for the selected sample, to reduce the number of simulations by 20 and maintain satisfactory results.

(3) The classification highlighted two main distinctions axis between buildings: active or passive, and adapted or not adapted to the extreme future. The proportional increase in average cooling needs could tomorrow transform several buildings considered passive today into active buildings (Phen1). On the other hand, a group of buildings that today have low needs will be particularly sensitive to future extremes (cluster 8). With a low average

exposure to needs, they may give the impression of being well adapted to future changes. However, they could present a health risk for their occupants exposed to high ambient heat from time to time (Phen2). Therefore, these buildings should receive special attention.

To distinguish one group of buildings from another, an analysis of the buildings characteristics should further be explored. A more heterogeneous population of buildings, extended to existing residential buildings should also be studied. Besides, It would be useful to extend this developed methodology to other RCP scenarios and other regions in France.

It should be highlighted that the huge number of calculations has been made possible by the existence of a database of buildings already modelled for dynamic thermal simulations (OPE). The data format is only compatible with a dynamic thermal simulation software (COMETH) which limits the possibilities of confrontation with other tools.

One of the limitations of this work is the 39 - years period used (the longer the period, the lower the internal variability). Another is the extreme years constructed considering extreme events over 5 days, another period could lead to different results.

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