Flexi-Sync

Flexible energy system integration using
concept development, demonstration and replication

REPORT ON ENERGY DEMAND, CLIMATE FLEXIBILITY AND RESILEINCE OF ENERGY SOLUTIONS FOR FUTURE CLIMATE

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ABSTRACT

This report is about analysing the climate resilience and flexibility of some of the demosites investigated in the Flexi-Sync project. The assessment is based on several future climate scenarios using regional climate models (RCMs) over a 90-year span of 2010-2099, considering climate uncertainties and extremes. A novel approach is developed to assess climate flexibility and resilience based on heating demand profiles and considering typical and extreme climate conditions over three periods of 2010-2039 (near future), 2040-2069 (mid future) and 2070-2099 (far future). Two indicators are developed for the purpose of this work, namely Climate Flexibility Indicator (CFI) and Climate Resilience Indicator (CRI). It is shown that accounting for flexibility based on 90th percentile of typical near future conditions, can address climate resilience of heating solutions on average, but the resilience of the energy system should be improved for 20-30% to the 90th percentiles of extreme cold events.

ACRONYMS

CDF	Cumulative Distribution Function
CFI	Climate Flexibility Indicator
CRI	Climate Resilience Indicator
ECY	Extreme Cold Year
EWY	Extreme Warm Year
GCM	Global Climate Model
GHG	Greenhouse Gas
IPCC	Intergovernmental Panel on Climate Change
RCM	Regional Climate Model
SSR	Sum Squared Regression
SST	Total Sum of Squares
TDY	Typical Downscaled Year
TMY	Typical Meteorological Year
IQR	Interquartile Range
XMY	Extreme Meteorological Year

1 INTRODUCTION

There is no standard definition of flexibility and resilience for energy systems and when it comes to climate, i.e., climate-flexibility and -resilience, definitions are less mature since the field is very new and developing. In our previous works, we have thoroughly investigated the concepts of climate flexibility [1] and climate resilience [2] (of which the latter was in connection to Flexi-sync), reviewing the available definitions and approaches to define and measure climate flexibility and resilience. A brief overview is provided in this section, however for a deeper overview the readers are referred to the relevant works of the author [1][2]. We also studied how climate change can affect renewable energy generation in five different European climate zones [3]. According to the results, the overall future PV and wind potential do not change considerably by climate change, however, impacts of climate uncertainties are considerable. In other words, the assessment depends a lot on what future climate scenario is selected. This is very important in connection to seasonal variations since the uncertainties associated with different climate scenarios considerably affect the renewable energy output.

Flexibility is defined in different ways, such as the ability to respond effectively to changing circumstances, the capacity for taking new action to meet new circumstances, the capacity to continue functioning effectively despite changes in the environment etc [4]. A number of definitions can be found for system flexibility in the energy sector [5]. System flexibility has often been discussed related to renewable energy integration from the perspective of power system operation [6]. In connection to future climate variations, we introduced flexibility of the energy system as the capacity of the system to resist performance degradation due to changes in the external environment [1]. However, the terms 'performance' and 'degradation' are quite open ended and might extensively depend on the application. For example, in this work, the focus will be mainly on heating demand due to the nature of the considered demosites, availability of data and assumptions for the performance of energy system.

The concept of resilience within the energy system domain is complex and multi-faceted [7] and can be used to address extraordinary conditions with different natures. Climate resilience is an emerging concept that is increasingly used to represent the durability and stable performance of energy systems against extreme climate events. Still, the concept has not yet been adequately explored in relation to the recent advances in climate change modelling [8]. Climate change will introduce changes to energy systems, affecting different aspects of the energy flow from generation to demand [9]. Most of these changes lead to considerable uncertainties in the energy infrastructure at different levels [10]. Output uncertainties are affected by demand conditions and uncertainties in building parameters, occupant behaviour, climate conditions, and control strategies [10,11]. The demand side uncertainties can get intensified in urban areas due to increased complexity, covering a wide range of concepts and disciplines, e.g. from building physics to social psychology [12]. Climate change and its uncertainties can affect the demand and generation sides considerably [13]. In Flexi-Sync, we have earlier investigated the impacts of extreme climate events and climate uncertainties on microclimate and the energy performance of buildings and urban energy systems [14][15][16].

The concept of climate resilience is introduced corresponding to situations that a system can function during (and/or after) extreme climate events. A resilient system should be able to respond to change and bounce back towards equilibrium or stability after an extreme event [17]. There is no standard definition for the resilience of energy systems [18] and it varies, depending on the context and objective. In general, a resilient energy system should speedily recover and learn from shocks and provide alternative means of satisfying energy service needs [19,20]. Resilience measures can be divided into two groups of short-term and long-term measures, with the former referring to preventive and corrective actions and the latter to planning for climate change adaptation [21].

Research works about the resilience of energy systems gain from the earlier works on the 'reliability', such as [22]. The reliability-oriented approach is mainly focused on the known threats, while the resilience-oriented approach also counts for extremes that may have not been experienced before [18]. Reliability often relates to 'low impact high probability' scenarios (which does not consider extremes) while resilience relates to 'high impact low probability' scenarios (also known as HILPs) [23]. This is also the difference between 'flexibility' and resilience [6][24]. Flexibility is usually addressed by accounting for high probability low impact scenarios, while resilience is attained when the energy system is prepared for diverse and partially 'unpredictable' factors by increasing its ability to withstand and recover from various disruptions (check Figure 1).

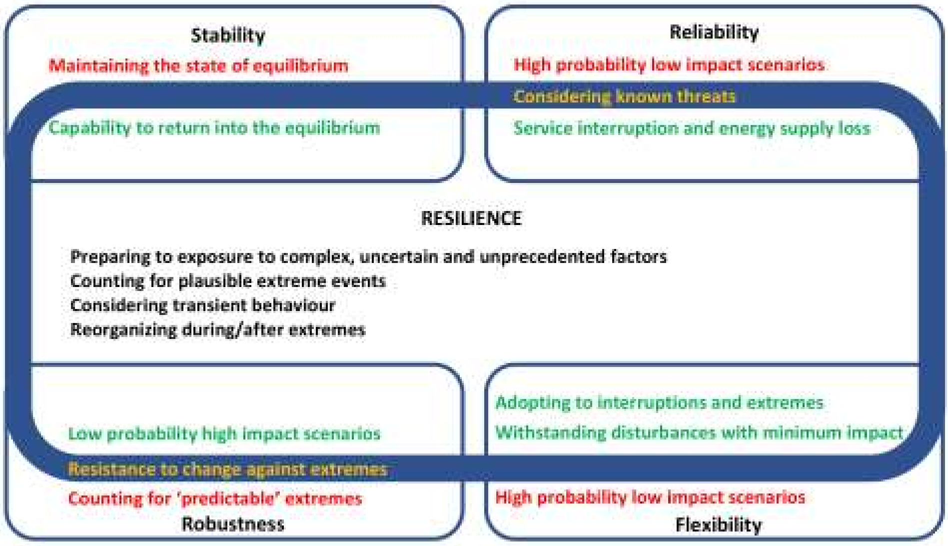

Figure 1. The specific characteristics of resilience (text in black) and its similarities (text in green and yellow) and differences (text in red) with stability, reliability, robustness, and flexibility. The yellow texts on the border of resilience are not always considered in studying resilience (figure from [2]).

Characterizing climate resilience is highly dependent on the considered infrastructure, phenomena, climate-induced risks, as well as spatial and temporal scales. General definitions for resilience such as the "ability to anticipate, absorb, adapt to and/or rapidly recover from a disruptive event" [25] provide enough space to select and/or define the characteristics and performance criteria that match the purpose of the assessment. Despite the considered characteristics, they should facilitate to avoid or minimize interruptions of service during extraordinary events. The characteristics that are counted in the literature for a resilient energy system can be divided into four major groups of 1) resisting, 2) adapting to, 3) preparing for, and 4) recovering from an extraordinary event. However, most of these concepts have been articulated without considering climate change and future climate modelling.

Planning for resilience requires the ability to predict the future and to understand the governing system dynamics. In an earlier work, we developed a novel framework to quantify climate resilience of urban energy systems considering climate uncertainties [26]. The key to the climate resilience assessment is the proper linkage between climate and energy models. Besides considering climate uncertainties, it is important to adopt a suitable temporal resolution for the analyses to reveal the risk of extreme events. This allows counting for 'unprecedented' extreme events which are physically 'plausible' and reflected by future climate models.

Climate is a very dynamic system and studying its behaviour highly depends on the selected temporal and spatial resolutions. The climate that affects citizens, buildings and energy systems in urban areas is urban climate, which is the altered version of the regional climate in a finer spatial scale. Variations in the global climate will be transferred to the urban climate (and even microclimate with much smaller spatial scales), affecting the performance of buildings and energy systems [14][15][16]. Depending on the urban design and morphology, climate variations can get amplified or dampened in the urban scale [27,28]. Currently, the climate research community have focused on global and regional climate models (GCMs and RCMs), while the urban scale model is rare and not coordinated. An RCM (normally with the spatial resolution of 10-50 km) is usually nested in a GCM (with the spatial resolution of 100-300 km) and driven by the conditions of the global climate at the boundaries of the RCM domain. It is well known that RCMs can reproduce a more realistic regional climate, especially with regard to extremes [29]. To assess the impacts of climate change on energy systems, meteorological data for the past/present (baseline or reference) and future climate are needed. While future climate information can only be provided by GCM and/or RCM, the past/present data climate can be represented by historical observations or GCM/RCM simulation for the historical climate. A common approach in energy studies is to use a one-year typical weather data set to represent climate over a 30-year period, known to be Typical Meteorological Year (TMY). TMY helps to represent typical conditions for the past/current climate and limits the calculation load; however, it is unable to fully represent extreme conditions. There exist different approaches for creating a typical or reference weather year, which the major ones are reviewed by Nik [13].

Assessing and quantifying the climate resilience of energy systems requires proper connection of future climate, projected by climate models, to energy models. Moreover, since becoming climate resilient demands withstanding the plausible abnormal conditions we need to know about the local climate with the hourly or sub-hourly temporal resolution and under many plausible future scenarios.

Future climate conditions are simulated by GCMs, adopting different initial conditions and forced by several forcing factors such as anthropogenic Greenhouse Gas (GHG) concentrations which depend on emission scenarios or concentration pathways (known as Representative Concentration Pathways or RCPs) developed by the Intergovernmental

Panel on Climate Change (IPCC) [30]. Due to the coarse spatial resolution of GCMs, and recognized biases, their output cannot be directly used in energy system analyses [31]. Therefore, downscaling is needed to simulate local weather conditions. Two main approaches for downscaling GCMs are dynamical and statistical downscaling [13]. Dynamical downscaling often involves using an RCM, whereas statistical downscaling builds on the statistical relationship between large scale climate and local climate established with the historical records. The latter approach only reflects changes in the average weather conditions and underestimates extremes. This is where dynamical downscaling can help, simulating weather data sets that are physically consistent across different variables and have suitable temporal and spatial resolutions [32]. Downscaling GCMs into different spatial resolutions result in different weather conditions. Moreover, the effects of urban and microclimate may induce considerable changes in the urban scale [33], which is hard, if not possible, to take into account by a conventional RCM.

All in all, the synthesized weather data will be different depending on the selected GCM, RCM, emissions scenario, GHG concentration (or RCP) and the spatial resolution. Consequently, it is not considered appropriate to rely on only a few numbers of climate scenarios. Moreover, relatively long periods (20 to 30 years) should be selected since the natural variability in the climate system is usually large. Therefore, short-term comparisons are not reliable [32]. This, together with the need for considering several climate scenarios, requires handling large data sets [13] which can become computationally expensive.

Access to representative and ready-to-use future weather files is another challenge for energy studies, which hopefully will fade away in the near future by the higher availability of future climate data sets and the increased interest in the energy sector. There are some ready-to-use weather data sets; however, they are mostly developed by extending the available approaches on the statistically downscaled GCM data. These data sets neglect future climate variations and anomalies and cannot represent extreme conditions. Therefore, they are not suitable for resilience studies. Fortunately, some approaches have been developed to consider extreme climatic conditions whilst keeping the calculation load affordable. For example, the weather generator of the UK Met Office, UKCP09, is trained using historical weather data and generates long-term weather data through random sampling. Crawley et al. [3] developed the Extreme Meteorological Year (XMY) using four combinations of extremes. Nik [13] developed a method for synthesizing representative future weather data sets out of RCMs, generating three data sets: Typical Downscaled Year (TDY), Extreme Cold Year (ECY) and Extreme Warm Year (EWY). The generated data sets include extreme conditions and overcome the challenge of future climate uncertainties by considering several climate scenarios, meanwhile keeping the calculation load limited. The same approach was adopted in this work. The application of the method has been compared with other available approaches and weather data sets [34] and verified against several types of simulations and impact assessments [13], including quantifying the impacts of climate change on urban energy systems [26].

2 METHODOLOGY

There is no standard method to assess climate resilience and flexibility of energy solutions [2]. In this work, a novel approach is developed based on the needs and availability of data. Since the majority of demosites in Flexi-Sync are located in heating dominated areas and a major assumption was that the energy supply at demosites will be enough to fulfil the demand, climate resilience and flexibility assessment approach is shaped around energy demand in relation to future climate variations. In this regard, the measured/past energy demand and weather data sets were used to extract the correlations between demand and outdoor temperature. The extracted linear regression equations were used to generate heating demand for future climate, considering typical and extreme climate conditions at the hourly temporal resolution. The calculated demand data were used to assess climate resilience and flexibility in the future.

To generate future weather data sets, the dynamically downscaled weather data out global climate models (GCMs) and using regional climate models (RCMs) were synthesized [35] [36]. Outputs of the 4th generation of the Rossby Centre regional climate model, RCA4 [37], is used in this work. RCA4 dynamically downscales five GCMs with the spatial resolution of 12.5km2: CNRM, MPI, ICHEC, IPSL, and MOHC [13] [38]. The synthesized RCM data were used to create typical downscaled year (TDY), extreme cold year (ECY) and extreme warm year (EWY) for three 30-year periods of 2010-2039 (near future), 2040-2069 (mid future) and 2070-2099 (far future) [13]. TDY, ECY and EWY (which together also called 'representative weather' data sets and 'Triple' when the whole data is used in the analysis) were used to generate hourly heating demand profiles for typical and extreme year over the three selected periods. The application of the approach has been verified for several type of building and energy studies (e.g. [34][39]) as well as microclimate (e.g. [27]) and energy system analysis (e.g. [16][26]).

To generate the hourly energy demand profiles, the linear correlations between the outdoor temperature and heating demand at each demosite (measured at the demosites) were implemented using TDY, ECY and EWY. The generated energy demand data were used to assess climate resilience and flexibility. To quantify **climate flexibility** in this work, the 90th percentiles of energy demand for typical weather conditions (TDY) are compared with each other in different periods as well as average values of ECY scenarios. The difference in percentage explains the change in (the need for) climate flexibility by climate change. To quantify **climate resilience**, the difference in the 90th percentile of energy demand for typical and extreme conditions are compared. Two specific indicators are introduced in this work, namely Climate flexibility Indicator (CFI) and Climate Resilience Indicator (CRI) which are defined as the following:

$$CFI = 100 \times \frac{P_{90}\left(HD_{TDY}^{nf}\right) - mean(HD_{ECY})}{mean(HD_{ECY})} \tag{1}$$

$$CRI = 100 \times \frac{P_{90}\left(HD_{TDY}^{nf}\right) - P_{90}(HD_{ECY})}{P_{90}(HD_{ECY})} \tag{2}$$

Where $P_{90}$is the 90th percentile of each parameter, HD_{TDY}^{nf} is heating demand in near future (2010-2039 in this case) for typical conditions (TDY), and $HD_{ECY}$is heating demand for extreme cold year (ECY).

3 RESUTLS

3.1 Future energy demand

Linear correlations between the measured (or simulated; both represent past climate) values of the outdoor temperature and heating demand were calculated. To have a better estimation, the values were divided based on the outdoor temperature, for example values for the outdoor temperature below and above 12°C. This is a standard part of data trimming/sorting to extract more consistent data-driven correlations. The coefficient of determination, or R^2, was calculated to make sure that the regression function predicts a good fit. For example, Figure 2 shows the linear fit of the hourly demand for temperatures below 12°C in Eskilstuna with R^2 of 0.93.

$$R^2 = 1 - \frac{sum\ squared\ regression\ (SSR)}{total\ sum\ of\ squares\ (SST)} \tag{1}$$

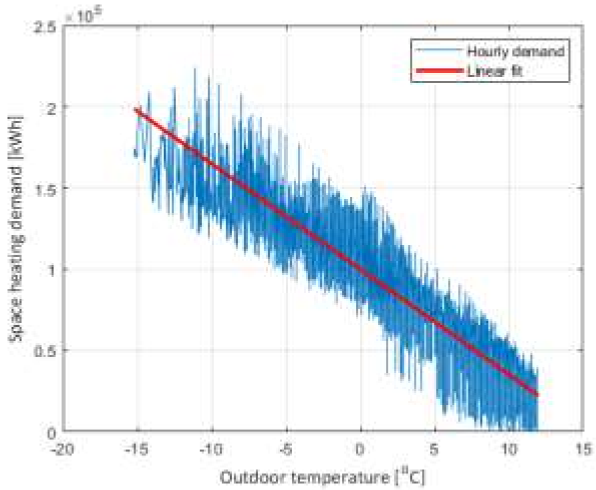

Figure 2. Sorted heating demand for Eskilstuna and the linear fit line, used as the estimation function to generate the future energy demand during three time periods.

The distribution of the measured (or simulated) space heating demand and the calculated one based on linear regression (also called 'data driven' data) are compared in Figure 3 using boxplots. As is visible, the data driven values accurately estimate the demand, which matches the measured/simulated one, considering the interquartile range (IQR), average and median values, as well as whiskers. In some cases, the extreme values and outliers might be missed, however this should not affect the climate flexibility and resilience analysis since extreme climate scenarios are considered in the analysis at the hourly temporal resolution. This is visible in Figure 4, where the measured and data driven values of heating demand in Maria Laach are compared. The hourly variations might be dampened in the data driven version (mostly during mild/warm seasons); however, this should not affect the resilience analysis since extreme scenarios at 90th percentile range are taken into account.

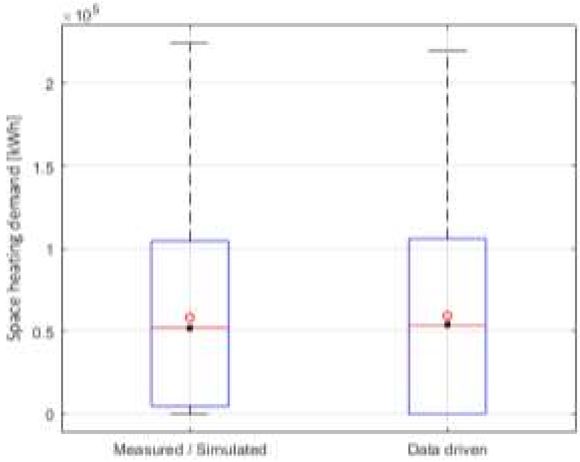

Figure 3. Comparing the distribution of the measured/simulated space heating demand in Eskilstuna with the estimated demand using the linear regression model (data driven). The red squares represent the average values and black dots the calculated standard deviations.

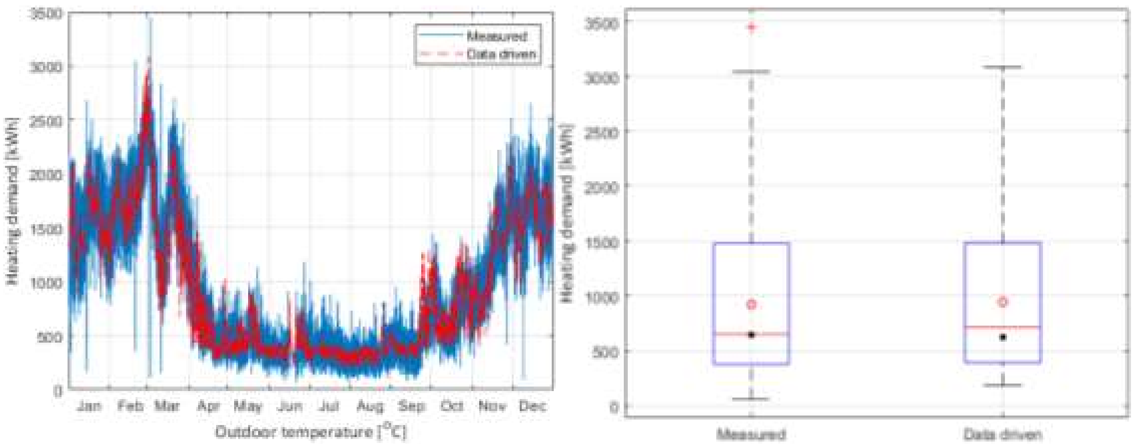

Figure 4. Comparing the hourly profile and annual distribution of the measured and estimated (data driven) heating demand in Maria Laach. In the boxplots, the red circles mark the average values and black dots the calculated standard deviations.

The hourly profiles of space heating demand in Eskilstuna are plotted in Figure 5 for past climate and three time periods considering typical and extreme conditions: TDY, ECY and EWY. As visible, during extreme cold conditions (ECY) the hourly values move considerably beyond the past and typical conditions. Judging based on typical conditions; the average heating demand will decrease in the future. This is also visible in Figure 6 ('heating demand' includes also hot water demand); smaller IQR and whiskers as time moves on. However, extreme values (e.g., outliers in Figure 6) can push the energy system. Although such extremes are usually neglected when designing flexible systems, but they should be considered when the aim is enhancing the climate resilience of energy systems.

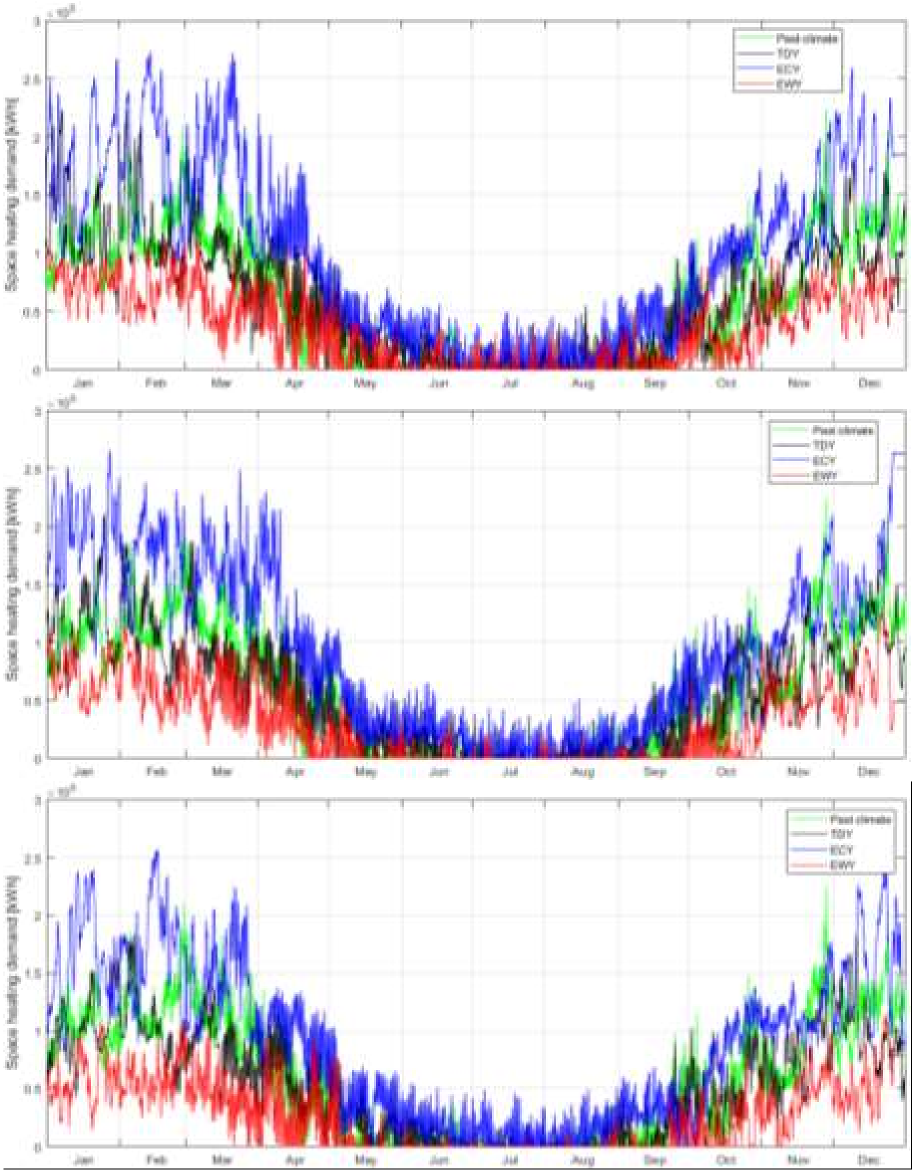

Figure 5. The hourly profiles of space heating demand in Eskilstuna for three time periods, considering typical (TDY), extreme cold (RCY) and extreme warm (EWY) years.

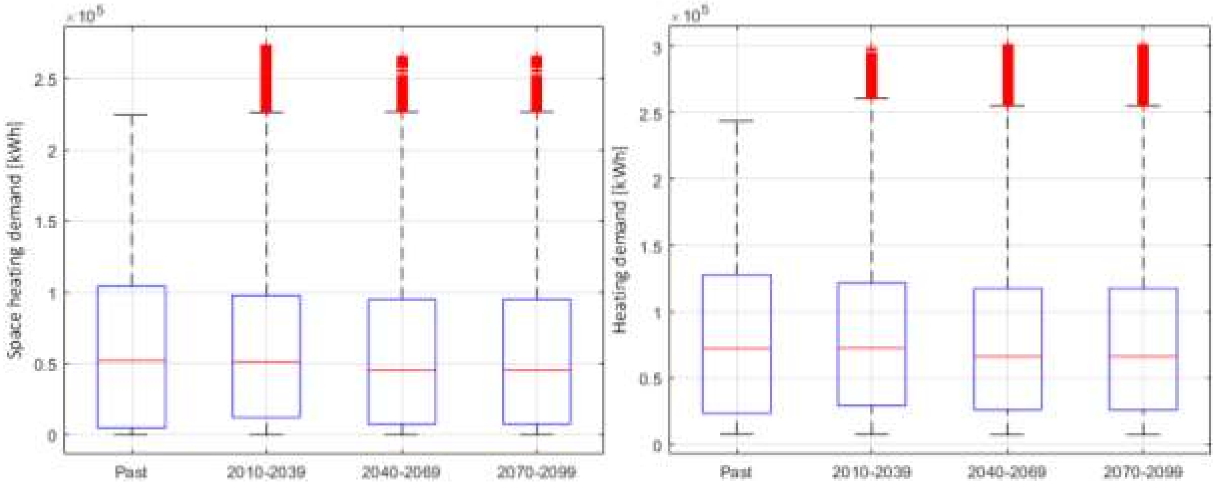

Figure 6. Comparing the distribution of the (left) space heating demand and (right) total heating demand (space and hot water heating demand) over past climate (2018) and three future periods in Eskilstuna.

Plotting the boxplot of the space heating demand at the monthly scale (using the hourly demand values) helps to get a better picture about the differences between typical and extreme conditions over time and in comparison to the past conditions, as in Figure 7. The advantage of such assessment at the monthly scale is that all the plausible conditions are considered at each month, without becoming very pessimistic. As described in [13], the ECY and EWY scenarios are pessimistic scenarios that accumulate all the extreme months together, therefore the probability of having such extreme year is quite low. However, each scenario per month in ECY and EWY, has exactly the same probability of occurrence as the other months. For example, we have considered 13 future climate scenarios and 30-year period to pick the extreme cold January. Each of the 390 (=13x30) Januaries has the probability of 1/390 and by selecting the coldest one, we do not overestimate. Consequently, each month can be treated as a plausible future condition. Knowing this, we can see that building robust energy system requires considerable investment, while by enhancing its climate resilience through increased flexibility, we can (or should) plan for winters much colder than the typical past conditions. Over time, the extreme values decrease (check ECYs in Figure 7 between the three periods). A similar comparison in Figure 8 for heating demand (space heating demand together with hot water demand) in Eskilstuna over three periods.

Figure 9 shows the hourly profiles of heating demand in Maria Laach while Figure 10 compares the distributions at the monthly scale. In this case also the heating demand will decrease by time, both the average values and the extremes. Meanwhile, extremes are still large enough compared to past climate conditions, making it impossible to neglect them when planning for climate resilient energy solutions.

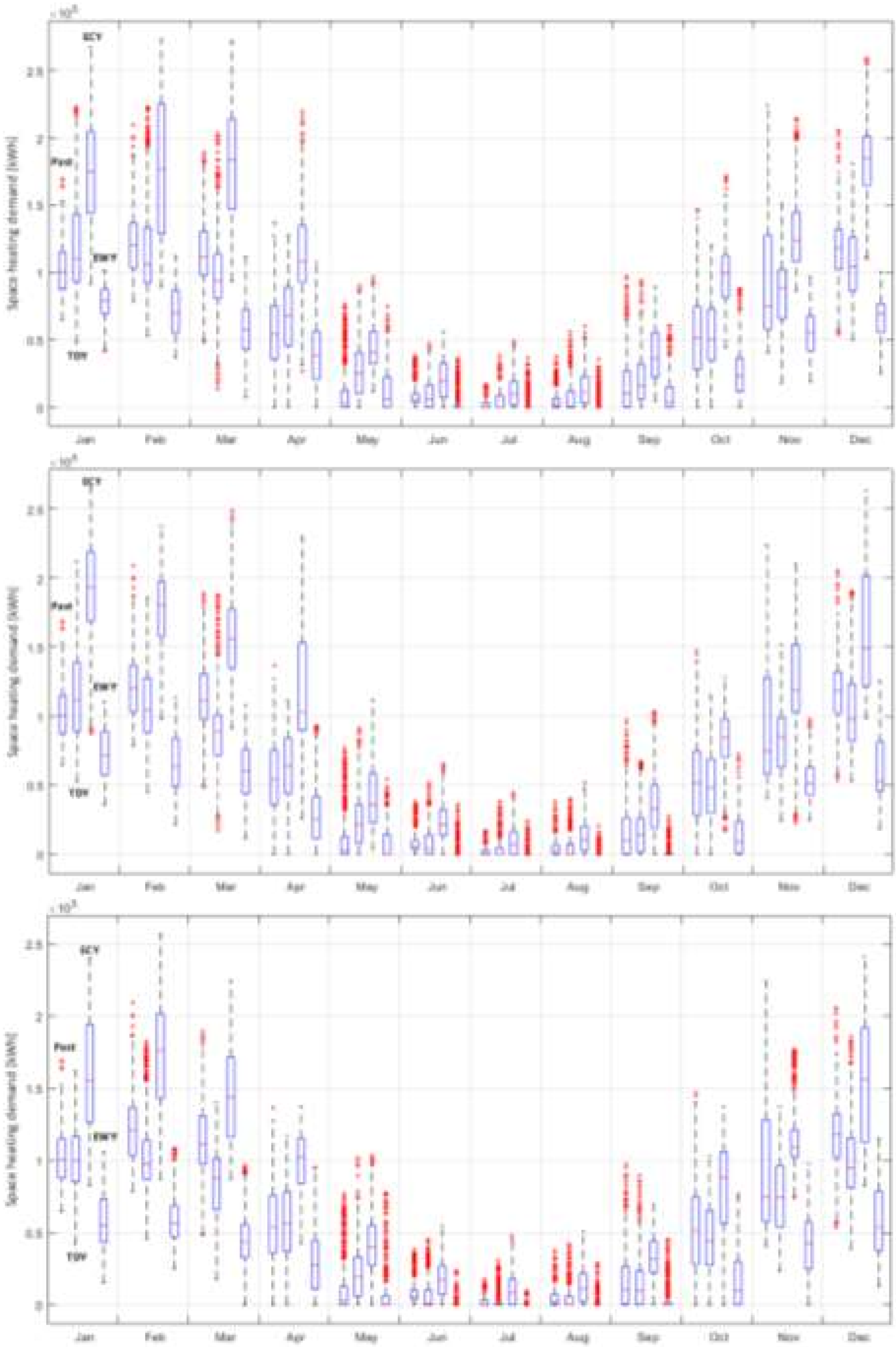

Figure 7. Comparing the distribution of the hourly space heating demand for typical and extreme weather scenarios over twelve months in three time periods in Eskilstuna.

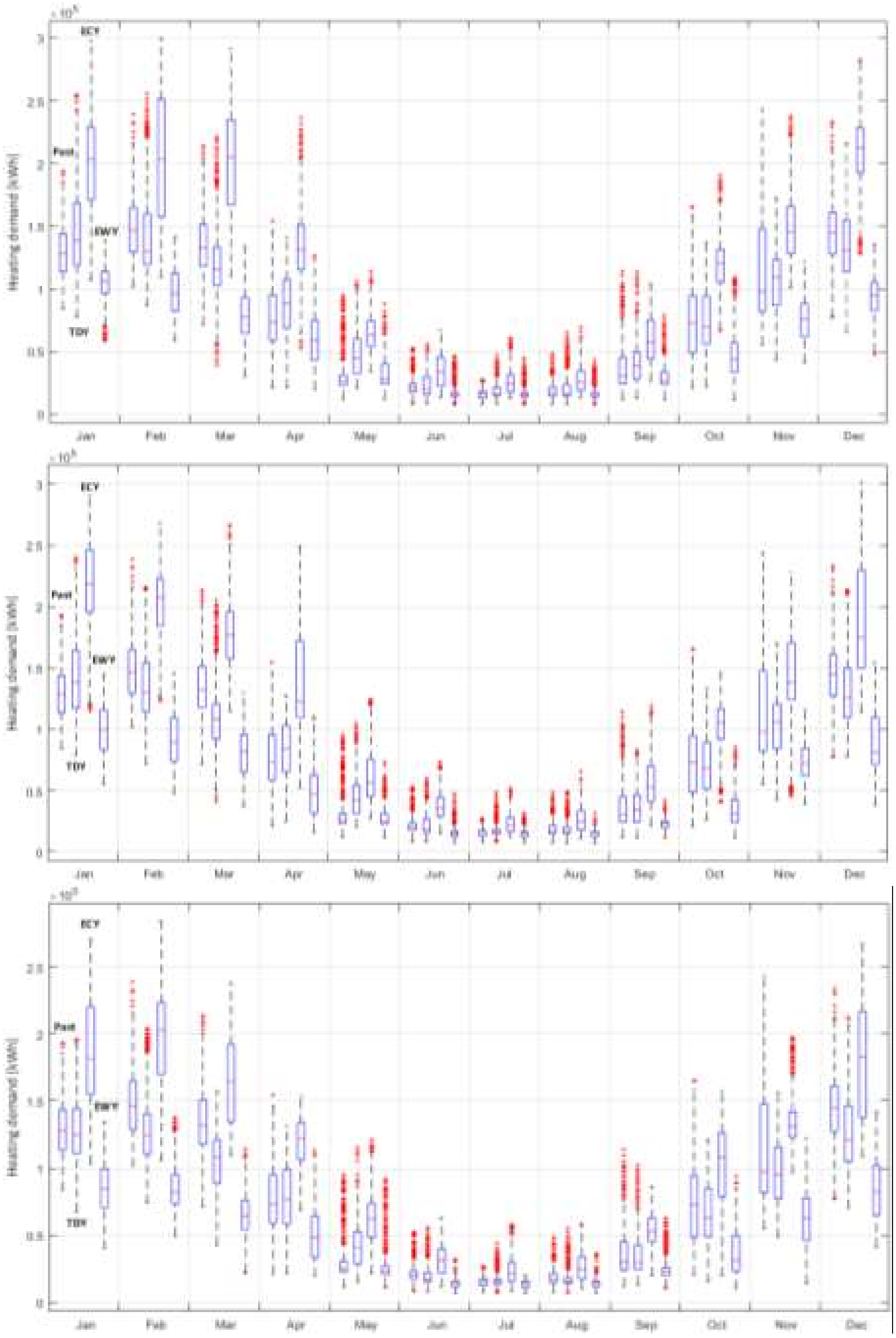

Figure 8. Comparing the distribution of the hourly heating demand for typical and extreme weather scenarios over twelve months in three time periods in Eskilstuna.

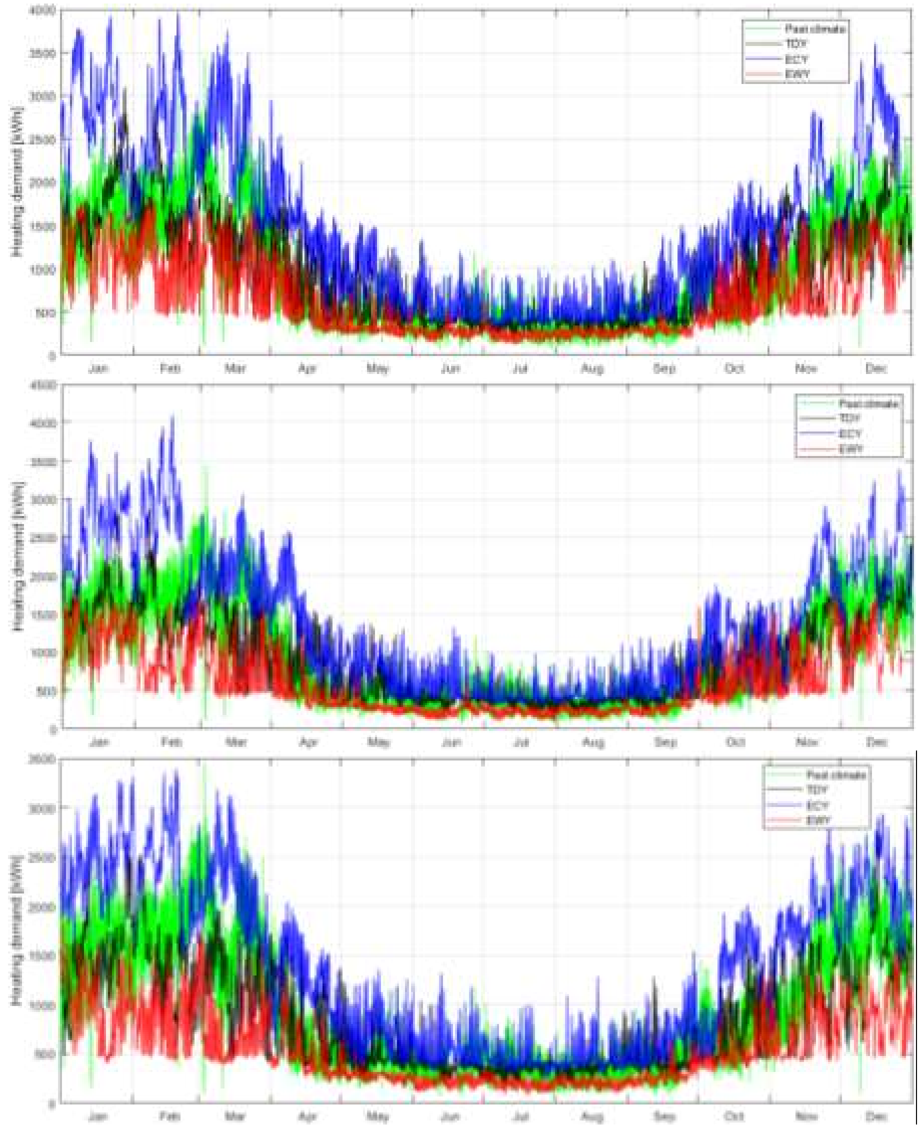

Figure 9. Hourly heating demand for three time periods, considering typical (TDY), extreme cold (RCY) and extreme warm (EWY) years in Maria Laach.

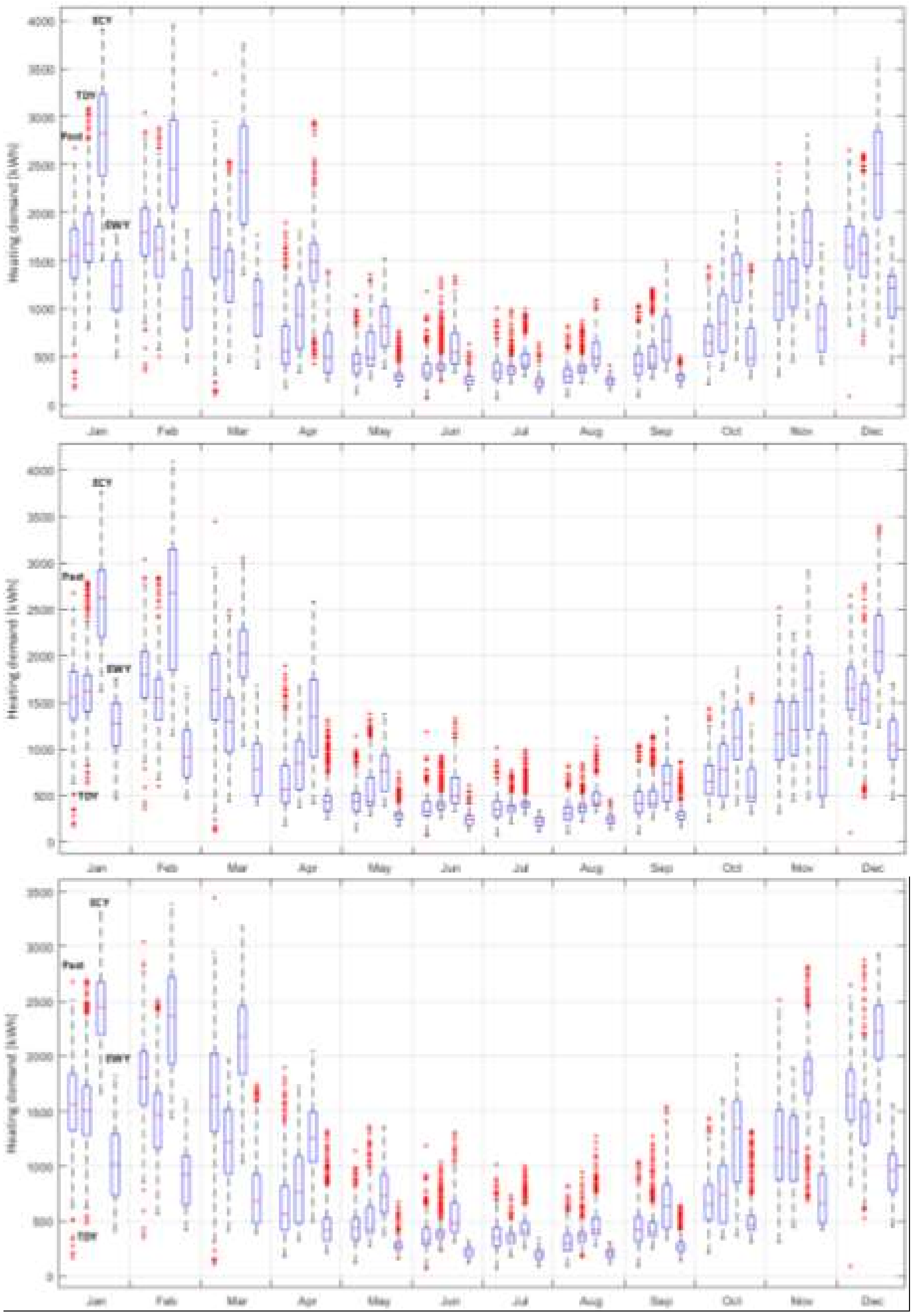

Figure 10. Comparing the distribution of the hourly total heating demand (space and how water heating demand) for typical and extreme weather scenarios over twelve months in three time periods in Maria Laach.

Future heating demand in Berlin at the monthly scale is shown in Figure 11 over 2040-2069 (which is also called near future). Naturally, ECY has much larger monthly heating demands compared to TDY. However, the common approach is designed based on typical conditions (TDY). This needs to be changed when designing climate resilient energy systems. Similar patterns were found over multiple European cities in five different climate zone over Europe, considering their energy demand [40].

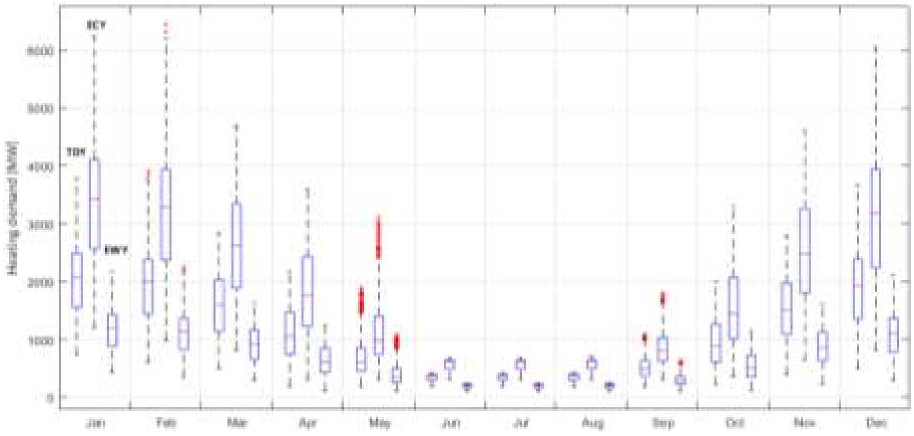

Figure 11. Comparing the distribution of the hourly heating demand for typical and extreme weather scenarios over 2040-2069 (representing 2050) in Berlin.

3.2 Climate flexibility and resilience

As discussed earlier, there is no standard approach to assess climate flexibility and resilience. A very simple approach is to study the mismatch between energy supply and demand, as shown in Figure 12 and Table 1 for Berlin over 2040-2069 (mid future). As visible, the number of mismatch hours is larger in the case of having extreme weather events. In Figure 12, the mismatch in ECY is limited, but critical since the demand is higher. In EWY, generation is higher is summer due to small heating demand and more renewable generation. It is important to consider that we do not investigate the performance of the energy system here, e.g. the extra generation can be stored or even stopped. As is shown in Figure 13, the extreme cold week shifts in ECY and having a wider range. However, since the assumption has been expansion of the energy system to cover the demands, such analysis will not provide enough information. Therefore, the focus is mainly on energy demand hereafter in the analysis.

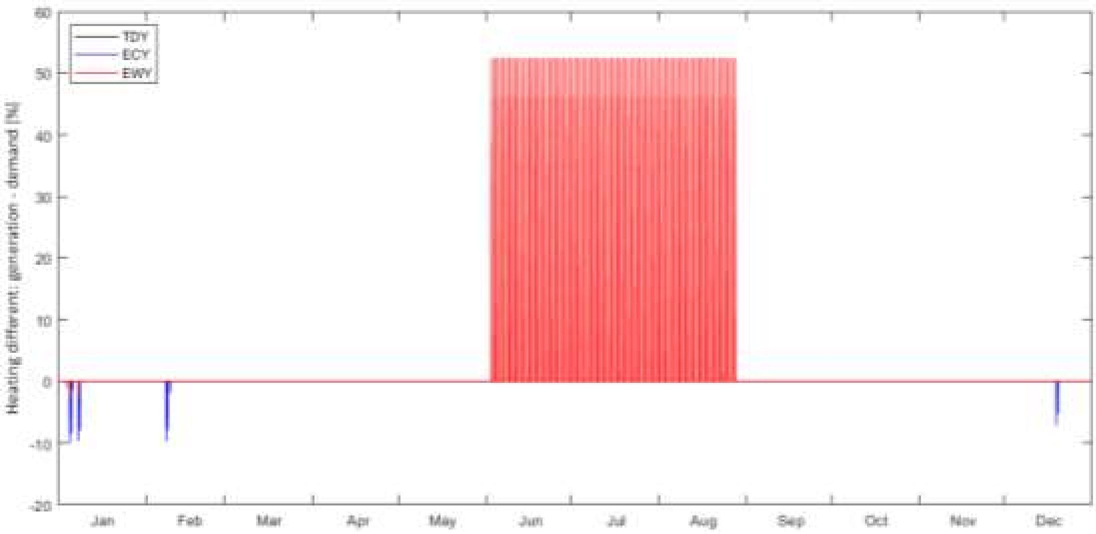

Figure 12. Difference in heat generation and demand (generation - demand) for typical and extreme weather scenarios over 2040-2069 (representing 2050) in Berlin.

Table 1. Berlin: Hours and percentage of energy mismatch (demand-supply) during typical and extreme cold conditions.

TDY		ECY	
Time [h]	Energy mismatch [%]	Time [h]	Energy mismatch [%]

102	-5.5	102	-8.4
103	-7.3	103	-10.1
104	-5.6	104	-8.4
105	-1.7	105	-4.6
116	-3.6	115	-2.6
117	-5.5	116	-6.5
174	-5.0	117	-8.3
175	-6.8	127	-1.3
176	-5.0	174	-7.9
177	-1.2	175	-9.6
188	-3.1	176	-7.9
189	-5.0	177	-4.1
918	-2.7	187	-2.1
919	-4.9	188	-6.0
920	-3.2	189	-7.9
932	-1.0	918	-7.8
933	-3.0	919	-9.7
8454	-2.1	920	-8.1
8455	-4.0	921	-4.2
8456	-2.1	931	-2.0
8469	-2.1	932	-6.1
		933	-8.0
		957	-1.8
		8454	-5.2
		8455	-7.0
		8456	-5.2
		8457	-1.4
		8468	-3.3
		8469	-5.2

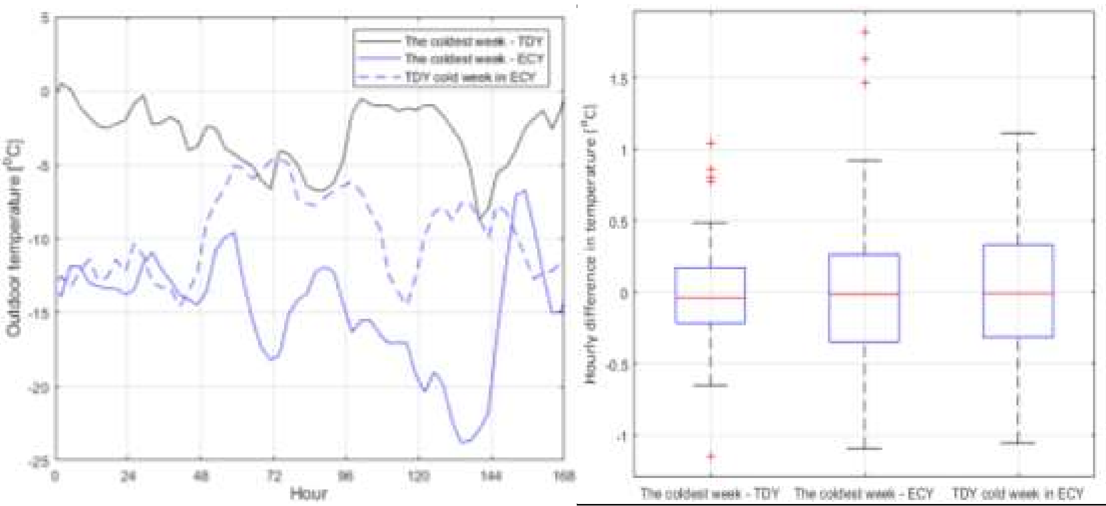

Figure 13. Comparing the coldest week in a typical year (TDY), an extreme cold year (ECY) and the situation of the TDY cold week in ECY over 2040-2069 (representing 2050). The average weekly temperature for the cases are -3.1, -14.8 and -9.6°C, respectively, with the standard deviations of 2.1, 3.8 and 2.9 °C.

As described in the methodology section, A novel approach is developed in this work to assess the climate flexibility and resilience of energy solutions based on demand. This includes the concept of comparison and assessment as well as two indicators. In the following, the assessment is based on the novel approach.

The monthly average, standard deviation and 90th percentile values of heating demand for TDY and ECY are compared over three periods for Eskilstuna in Figure 14 and for Maria

Laach in Figure 16. The relative difference of the values in the last two periods compared to 2010-2039 are plotted in Figure 15 and Figure 17. Assuming that the 90th percentiles of past climate (mainly considering typical conditions) are used to manage or design energy systems, then the 90th percentiles of TDY over three periods can give some idea about future conditions. As is visible on the left columns of Figure 14 and Figure 16, the 90th percentiles of TDY are quite at the same level of the past climate, with decreasing values over time. However, if we want to become climate resilient, we need to consider extreme events which are shown in the right columns of the figures. As is visible, the 90th percentiles of ECY are much larger than those for the past climate. For example, in Figure 14 the 90th percentiles of ECY in 2010-2039 are around 67% and 51% larger than the 90th percentile of past climate. These values decrease to 44% and 34% in 2070-2099, however still large enough to have in mind. The warming trend of climate is visible in Figure 15 and Figure 17 by comparing the values for two periods. The two figures show that the monthly averages, standard deviations and 90th percentiles of heating demand will mostly decrease in the future compared the 2010-2039 (or near future). It is also interesting to see that the average values of ECY reach to the same level of 90th percentiles of past climate. In other words, there is a good chance that if we design a flexible and resilient energy system to cover heating demands in the near future, it will perform well in mid and far future.

This is further investigated in Table 2 and Table 3, where monthly CFIs and CRIs are calculated for three time periods. CFI provides an indication about the climate flexibility of an energy system that is designed based on 90th percentiles of typical conditions (TDY) in the near future (2010-2039), in comparison to monthly average of extreme conditions (ECY). CRI provides an indication about the climate resilience of an energy system that is designed based on 90th percentiles of TDY, in comparison to 90th percentiles of ECY. As is visible in the tables, a flexible system designed considering the 90th percentiles of near future, can be considered climate flexible in the future (showing mostly positive CFIs over time), however it will not be 100% climate resilient and there will be around 20-30% uncertainty in meeting the extreme heating demand (negative CRIs). Accepting this risk, depends on the adopted strategies by the designers and/or decision makers.

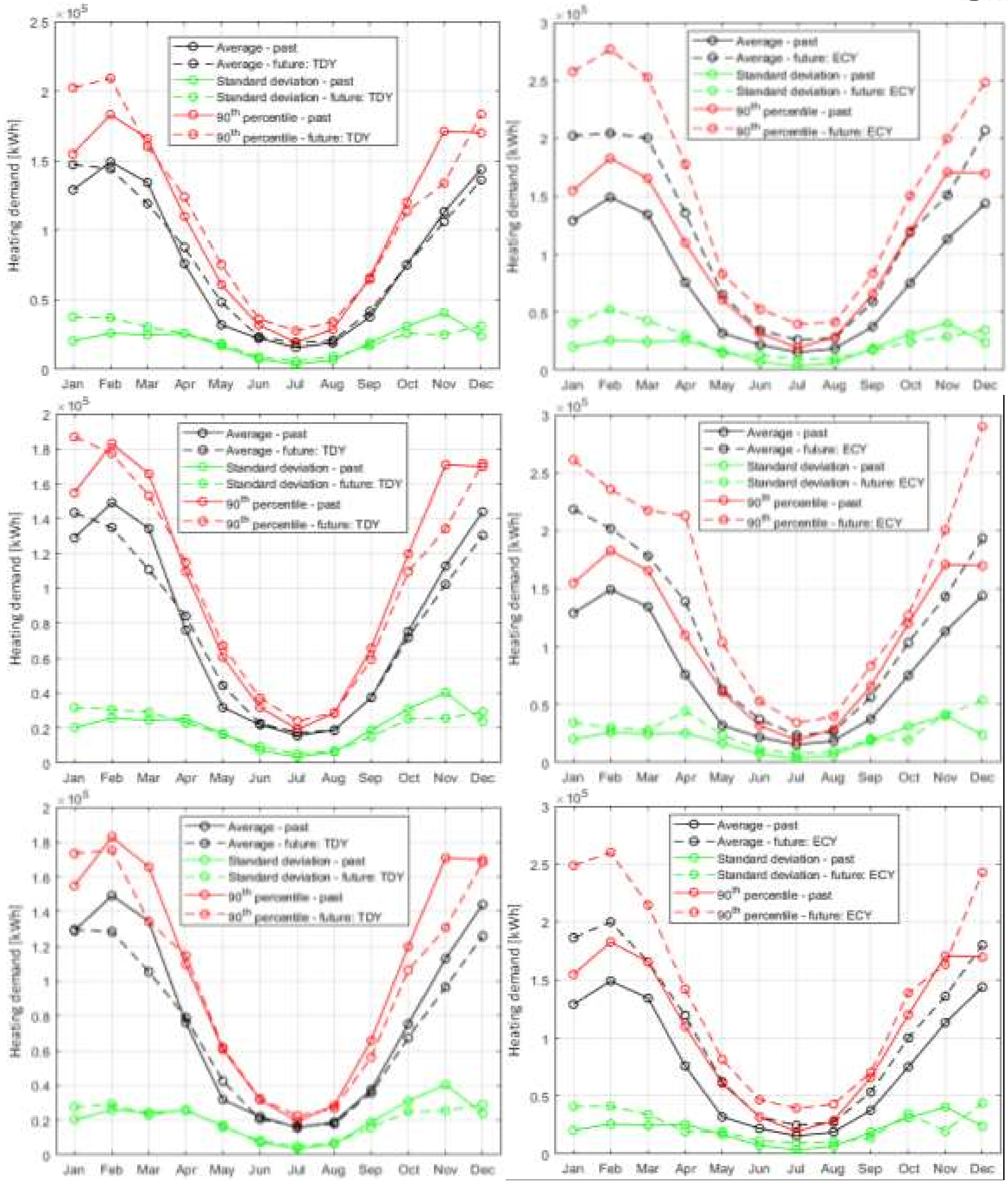

Figure 14. Comparing monthly average, standard deviation and 90th percentile values of heating demand for TDY (left) and ECY (right), in Eskilstuna during 2010-2039 (top), 2040-2069 (middle) and 2070-2099 (bottom).

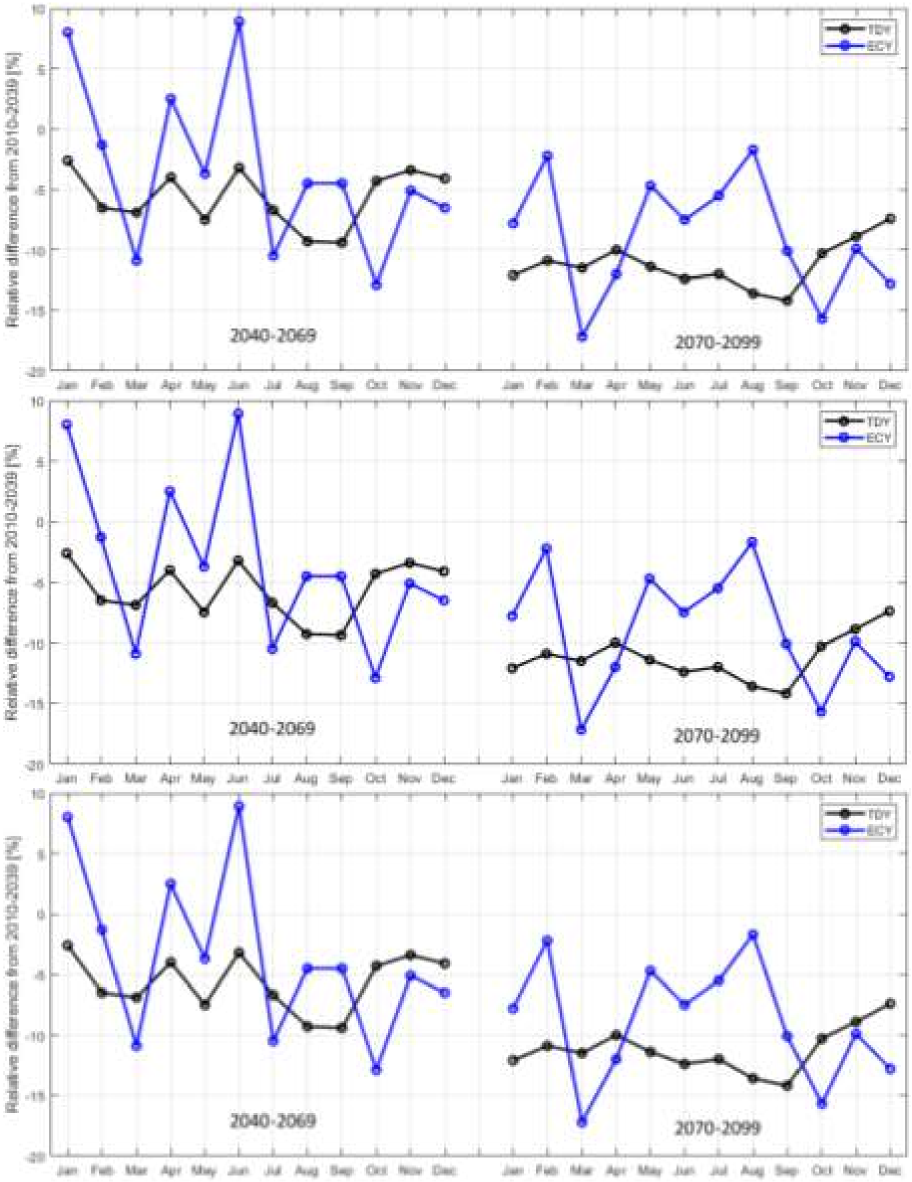

Figure 15. Relative difference in the monthly average (top), standard deviation (middle) and 90th percentile (bottom) heating demand in two periods compared to 2010-2039 in Eskilstuna.

Table 2. CFI and CRI for Eskilstuna [%]

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CFI	near future	0	2	-20	-9	16	5	6	23	9	-5	-11	-11
	mid future	-7	4	-10	-11	20	-3	18	29	14	9	-6	-5
	far future	8	5	-3	4	21	14	12	25	21	13	-2	2
CRI	near future	-22	-24	-37	-30	-9	-31	-31	-18	-23	-25	-33	-26
	mid future	-23	-11	-26	-42	-27	-32	-20	-14	-23	-11	-33	-37
	far future	-19	-20	-25	-13	-8	-23	-30	-20	-8	-18	-18	-25

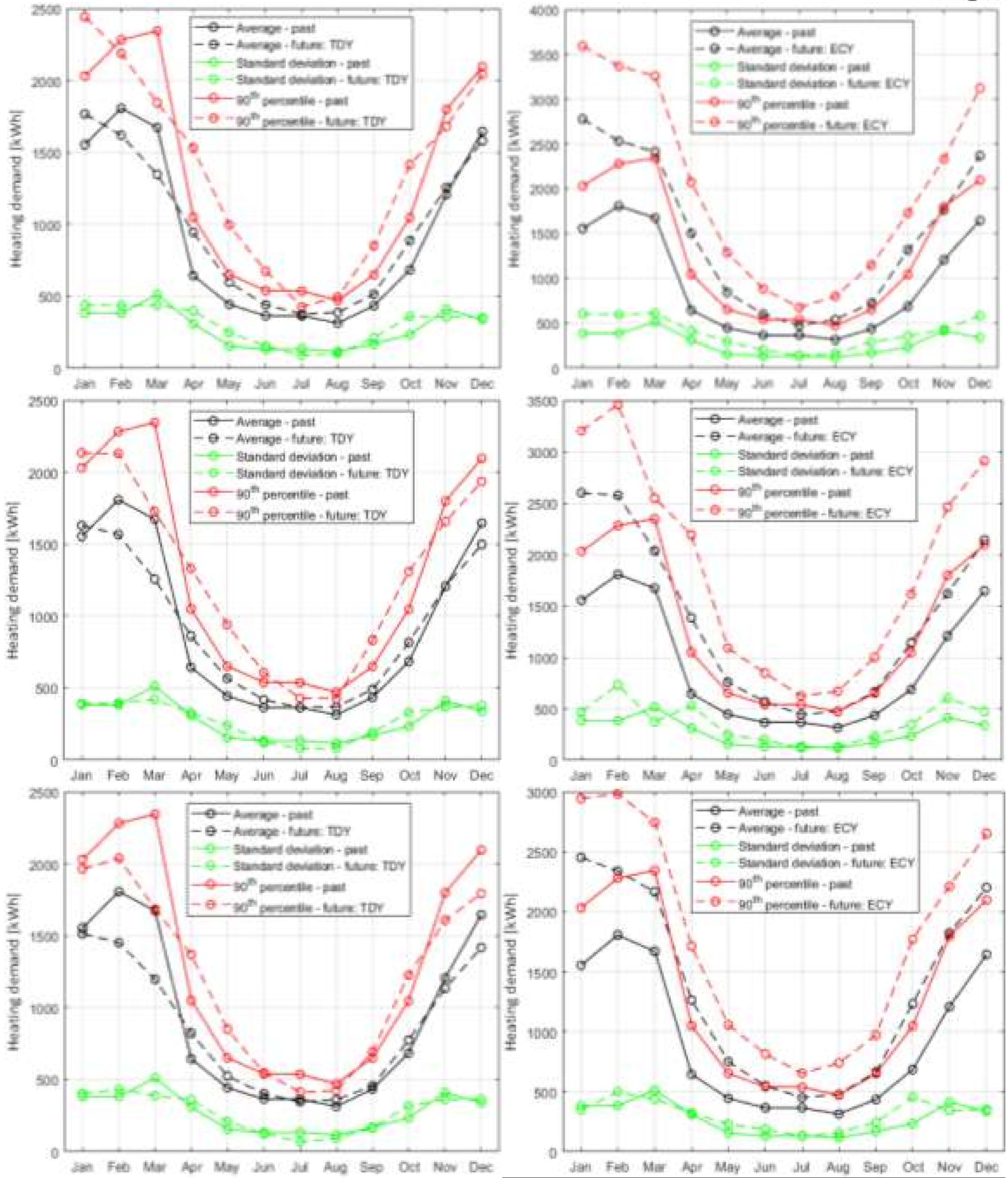

Figure 16. Comparing monthly average, standard deviation and 90th percentile values of heating demand for TDY (left) and ECY (right), in Maria Laach during 2010-2039 (top), 2040-2069 (middle) and 2070-2099 (bottom).

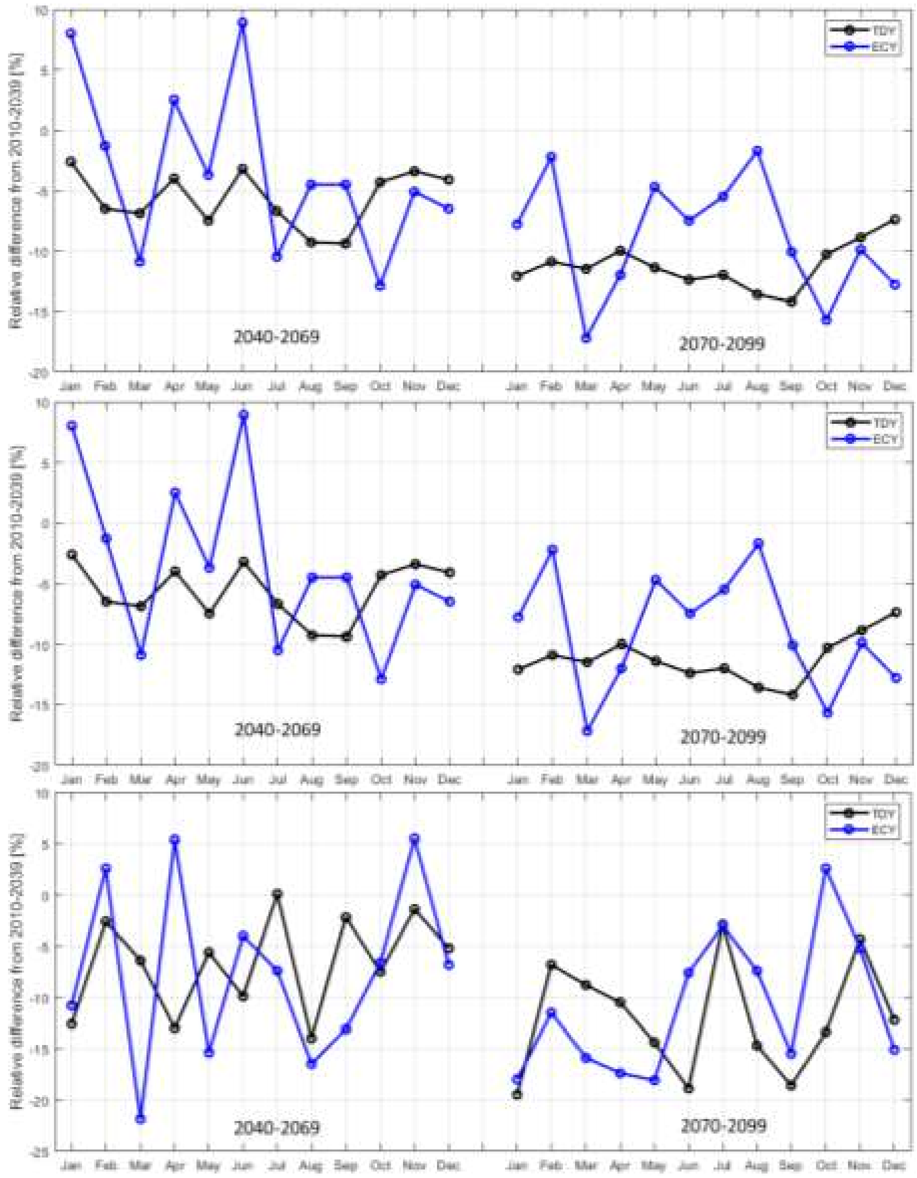

Figure 17. Relative difference in the monthly average (top), standard deviation (middle) and 90th percentile (bottom) heating demand in two periods compared to 2010-2039 in Maria Laach.

Table 3. CFI and CRI for Maria Laach [%]

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CFI	near future	-12	-14	-23	2	18	13	-9	-8	18	8	-5	-14
	mid future	-6	-15	-9	11	31	19	-3	5	29	24	4	-4
	far future	0	-7	-15	21	32	23	-5	4	28	15	-8	-7
CRI	near future	-32	-35	-43	-26	-23	-24	-37	-38	-26	-18	-28	-35
	mid future	-24	-37	-28	-30	-9	-20	-31	-26	-15	-12	-32	-30
	far future	-17	-27	-33	-11	-6	-17	-35	-33	-12	-20	-24	-23

4 CONCLUDING REMARKS

A novel approach was introduced in this work to assess and quantify climate flexibility and resilience of energy solutions for future climate, focusing on heating demand of buildings. The assessment was based on synthesizing multiple future climate scenarios using regional climate models (RCMs) over a 90-year span of 2010-2099, considering climate uncertainties and extremes. Typical and extreme weather data sets were generated to represent typical and extreme climate variations at the hourly temporal resolution over three periods of 2010-2039 (near future), 2040-2069 (mid future) and 2070-2099 (far future). For the purpose of this report, typical downscaled year (TDY) and extreme cold year (ECY) were mainly used. Future energy demand profiles were generated using linear correlations that were extracted from measured data. These profiles were used to assess future energy demand, climate flexibility and climate resilience for future climate.

To assess climate flexibility and resilience, a novel approach was developed based on heating demand profiles and considering typical and extreme climate conditions. Two indicators were introduced, namely Climate Flexibility Indicator (CFI) and Climate Resilience Indicator (CRI). Based on the analysis, a flexible system designed considering the 90th percentiles of near future, can be considered climate flexible in the future (showing mostly positive CFIs over time). There is a good chance that if we design a flexible and resilient energy system to cover heating demands in the near future, it will perform well in mid and far future. However, it will not be 100% climate resilient and there will be around 20-30% uncertainty in meeting the extreme heating demand (negative CRIs). Accepting this risk, depends on the opinion of the designers and decision makers.

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