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Challenges resulting from urban density and climate change for the EU energy transition

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EU energy transition: challenges resulting from urban density and climate change

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Abstract

Dense urban morphologies further amplify extreme climate events due to the urban heat island phenomenon, rendering cities more vulnerable to the effects of extreme climate events. We developed a modelling framework using multiscale climate and energy system models to assess the compound impact of future climate variations and urban densification on renewable energy integration for 18 European cities. We observed a marked change in wind speed and temperature due to the aforementioned compound impact, resulting in a notable increase in both peak and annual energy demand. Therefore, an additional cost of 20%–60% will be needed during the energy transition (without technology innovation in building) to guarantee climate resilience. Failure to consider extreme climate events will lowers power supply reliability by up to 30%. Energy infrastructure in dense urban areas of southern Europe is more vulnerable to the compound impact, necessitating flexibility improvements at the design phase when improving renewable penetration levels.

Keywords: Energy systems, Climate change, Urbanization, Extreme weather events

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Cities play a major role in global economic growth; they are estimated to generate more than 60% of total GDP growth by 2060 and accommodate an additional 2.1 billion people by 2050.[1] The economic contribution of urban areas comes at a high carbon cost, being responsible for 70% of global anthropogenic CO_2 emissions, and expediting climate change that leads to more frequent and intense extreme weather events.[2,3] These extreme events markedly increase the mortality rate in urban areas and retard economic growth.[4] By 2050, cumulative damage from climate change may reach $8 trillion, retarding GDP growth by 6.6% by 2100.[5,6] Therefore, improving climate resilience and sustainability in cities, while facilitating urban densification, is a significant challenge that requires immediate attention.[7]

Transformation of the energy sector is vital to improve sustainability and climate resilience in cities. The multi-faceted impacts of climate change and probable cascading failures make the sustainable transition of the energy sector more challenging.[8,9] For example, energy demand in buildings will increase considerably during extreme climate events (by up to 400% for cooling energy demand only), increasing the probability of power supply breakdown.[10] Complexities in the urban environment also make it more difficult to address energy issues while accommodating the challenges brought about by climate change.[11] High-rise buildings, pavements, and other surfaces in urban areas form urban canyons, significantly reducing the wind speed within cities while absorbing and retaining heat, which leads to an increase in temperature.[12,13] This phenomenon is known as an urban heat island, which markedly increases the cooling energy demand (by up to 40%) by further magnifying the impact of extreme climate events.[14]

Understanding the compound impacts resulting from future climate variations and increased urbanization requires multiscale (spatiotemporal) climate–energy system models.[15] For example, building energy models coupled to urban and microclimate models offer refined and accurate details regarding the heating and cooling demand at high spatiotemporal resolution.[16] These models help to quantify the impact of extreme climate hot/cold (low-probability high-impact (LPHI)) events on the energy sector with improved accuracy. However, these models do not possess the capability to consider long timescales due to computational limitations.[9] In contrast, building energy models linked to global and regional climate models focus on long-term climate variations with spatial resolutions that are coarser than the urban scale.[17,18] The compound impacts of future climate variations and urbanization on energy demand are not quantified in these models.[9] Therefore, multiscale (spatiotemporal) models are required to quantify the challenges brought about by combinations of climate change and urban densification. Existing energy system sizing models are not compatible with such multiscale inputs that have different spatiotemporal resolutions[19]. In addition, energy community solely relies on a single representative meteorological time series (or a single set (in the case of stochastic models)) which cannot represent a broad range of challenges brought by future climate variations such as HPLI and LPHI events in the urban context [19]. In this context, the present study show that energy systems become vulnerable to extreme climate events as we move along the energy transition, or a considerable drop in performance occurs when moving from the design to operation phases (performance gap). Energy infrastructure in dense urban areas in the southern part of Europe is more vulnerable to the compound impact than in the central and northern cities, which makes it important to further improve the flexibility of energy infrastructure to facilitate renewable energy integration. Therefore, it is important to devise design pathways to further expand urban areas that are both sustainable and climate resilient.

Considering multiscale spatiotemporal inputs

We here introduce a modeling platform linking climate, building simulation, and energy system models to enable the simulation and evaluation of the energy transition of cities, ensuring urban resilience to future climate variation and urban densification (Fig. 1). A multiscale climate–building energy approach (to consider different spatiotemporal resolutions) was developed to couple regional, urban, and microclimate models with a building simulation model. The platform enabled us to consider the compound impacts of future climate variations and urban densification (brought at different spatiotemporal resolutions) on energy demand. A set of energy demand and renewable energy generation profiles that reflect typical variations (reflecting seasonal variations), high-probability low-impact (offsets from seasonal variation) (HPLI) and LPHI extreme climate events, were obtained from our multiscale modelling. These profiles were then used as the inputs to the energy system model consisting of deterministic, stochastic, and robust elements. The compound energy system model (Comp) reflects the challenges resulting from the compound impact of future climate variations and urban densification on renewable energy integration and resilience of the energy infrastructure. The concept of urban archetypes was used to represent the complexity of the urban morphology of 18 cities in Europe.

Representing the impacts of future climate variations

As well as long-term changes in climate, such as an increase in the average global temperature, climate change brings about climate variations and induces increasingly frequent and strong extreme climate events (LPHI)[7]. These notable changes in typical climatic conditions can easily lead to a marked increase in energy demand while simultaneously curtailing energy generation, ultimately resulting in a blackout.[17,20] We developed a method to account for extreme events (LPHI) and climate uncertainties[10] and expanded that further to address HPLI events and seasonal variations.[17,20] Seasonal climate variability (introduced as a typical variation) can be viewed as fluctuations in the seasonal cycle induced by higher frequency processes.[21] Inspired by a method presented by Fischer and Schär,[22] we studied seasonal variabilities in energy simulations[23] taking into account anomalies. Anomalies show how much each hour in a season deviates from the average value for that hour in the season considering all the climate scenarios presenting HPLI. For example, Fig. 2 shows hourly values and anomalies on a seasonal basis for outdoor temperature in Belgrade and wind speed in Stockholm. Furthermore, we also compared the distributions of these values for five representative cities covering four climate zones across Europe.

As seen in Fig. 2e and g, the range of climate variables projected by all the climate scenarios (390 years) is mostly covered by the typical and extreme weather data sets; however, this is not the case for the calculated anomalies (Fig. 2f and h). Although the 5th and 95th percentiles of the representative weather data sets (typical and extremes together) in Fig. 2f and h predict values close to the complete

390 years of regional climate model (RCM) data, there remain extreme anomalies in the RCM data that are not captured by the representative weather data sets (compare the outliers of the grey boxplot with other boxplots in Fig. 2f and h). These anomalies are considered through HPLI events in addition to the typical and extreme events (LPHI) during the design process.

Future climate variations notably influence energy demand. Five cities, namely Athens (Mediterranean climate), Madrid (Mediterranean climate), Belgrade (humid subtropical climate), Paris (marine west coast climate), and Stockholm (humid continental climate), representing the four main climate zones in Europe (based on Köppen classification),[24] were selected to further assess the impact of future climate variations on energy demand.[24] The probable future energy demands under the impacts of synthesized weather data (extreme cold year (ECY), typical day year (TDY), and extreme warm year (EWY)) were assessed for the five representative cities over the period 2010–2099. As shown in Fig. 3, higher cooling demand can be observed for cities in each of the four climate zones in Europe. For example, the average annual cooling demand in TDY for Athens and Belgrade is predicted to be over 3 and 3.9 times higher, respectively, in 2070–2099 compared to 2010–2039 levels. The average cooling demand in an extremely warm month is over 2.7 times higher than in TDY. Therefore, it is clear that future climate variations will have a considerable impact on both heating and cooling demand, and these demands tend to evolve further as we move forward in the timeline.

Influence of urban density on energy demand

An urban climate model (UCM) linked to RCM data (Meso) was used to understand climate variations brought about by the morphology of urban areas. The urban morphological parameters (e.g., density and sky view factor) and building characteristics that influence the urban climate were represented by urban archetypes for 18 cities. Among them, five cities were taken (same as above) to further illustrate the impact of urban climate on energy demand. As shown in Fig. 4a–c, a notable reduction in wind speed was brought about by the urban boundary layer. The deviation in wind speed was observed in typical (TDY) as well as in extreme scenarios (ECY and EWY). Urban morphology of the archetypes results in a lower average wind speed and a higher average ambient temperature (Fig. 4d–f). An increase of up to 1.3 °C in the annual average temperature was observed for ECY, while increases of up to approximately 1.2 °C were observed for TDY and EWY. The impact was much stronger at an hourly temporal resolution, inducing temperature differences of up to 10 °C.

The link between the UCM and the urban microclimate model (UMM) helps to investigate climate variations at the microscale (urban canopy layer) at finer spatial resolution. The UMM downscales climate variables from the mesoscale to the microscale, while also considering anthropogenic heat emissions from buildings and occupants. As shown in Fig. 4g and i, further changes in wind speed and air temperature were observed when improving the spatial resolution during extreme warm days (EWD) and extreme cold days (ECD). Unlike UCM, which provides a single value for the urban canopy layer, UMM estimates wind speed profiles within narrow and wide urban canyons (based on the peak cooling and heating days of the year). This will lead to a higher time-averaged wind speed compared to UCM, while lower wind speed magnitude can be seen within narrow urban canyons (further comparison of these two models are presented in Supplementary note 13). This will lead to lower thermal circulation and heat removal within narrow canyons, resulting in higher air temperature. Consequently, a temperature increase of 6%–17% during the peak cooling period from UMM results can be observed, compared to UCM, for the five cities (Fig. 4h and j). Changes in wind speed and temperature due to the urban morphology and high spatial resolution UMM can influence the energy demand of buildings, especially during extreme events, as shown in Fig. 5a–d. The compound impact of longer summer periods having an extremely warm climate and dense urban configuration will markedly increase the average cooling demand, especially for Madrid, Athens, and Belgrade. Such urban centers are much denser than the European average (according to the Urban Centers Database),[9] with Madrid, Athens, and Belgrade having 6194, 7568, and 4670 inhabitants/km^2, respectively, compared with 3305 inhabitants/km^2 for the European average. For example, the average cooling demand rises by 15% and 28%, for Athens and Madrid, respectively, when moving from the Meso to UCM (Fig. 5b) (Athens and Madrid are the first and third most densely populated capital cities of the EU, respectively). The impact of urban climate on energy demand is not uniform throughout the demand profile. A marked increase and fluctuation in peak demand can be observed for cities with higher urban density, such as Madrid and Belgrade (Fig. 5b and d). These changes lead to a marked change in the hourly demand profile, as shown in Fig. 6a and b. In addition, peak energy demands further increase when considering microclimate conditions (6c–h). For example, the peak cooling demand during the hottest day of the year in Madrid increases by 30% when moving from the urban scale to the microscale (Fig. 6f). Failure to account for microclimate and neglecting such a considerable increase will result in an underestimation of the impacts of climate variations and lead to non-resilient urban energy systems[9]. The influence of urban climate on energy demand is clearly shown for the 18 cities across different parts of Europe (Fig. 5e). There is a marked deviation between heating and cooling demand obtained from Meso and UCM models whenever the urban morphology is more complex. More specifically, in addition to density, average sky view factor (SVF) and average building height, material properties, occupancy profiles, and climate of each city (heating or cooling dominated) also play a major role in the deviation between heating and cooling demand. Therefore, considering the compound impact of future climate variations and urban configuration is essential to guarantee the climate resilience of cities.

Impact of different climate phenomena on the energy system

The urban energy systems in European cities were assessed using an energy system model that provides the optimal design (the outline of the energy system considered is presented in Supplementary note 5) and operation strategy (dispatch) for an energy hub. Net present value (NPV) and grid integration (GI) levels were considered as the objective functions, while power supply reliability was taken as a constraint to guarantee a consistent power supply. NPV assesses the financial aspect of the project while GI level determines the autonomy of the energy system (see Methodology and Supplementary note 7). Onsite renewable energy technologies will improve the autonomy level, reduce the GI level, and make the system less dependent on the transmission network. The Pareto front of NPV and GI (Fig. 7) shows all the non-dominant sets of design solutions (spectrum of alternatives) trending towards the minimal cost and maximum autonomy.

The Det and Det–U models presented in Fig. 7a–e uses a deterministic model in the energy system optimization; Det does not consider the influence of urban climate (details about the classification are presented in Supplementary Note 8). Comparisons between Det and Det-U reveal that urban climate is influential (line A–A in Fig. 7b) in all cities except Stockholm and Paris (regions B and C in Fig. 7d and e), where the urban climate has only a trivial impact on the Pareto front. This is due to the lower density in Stockholm and the seasonal variability in the weather pattern that offsets the increase in energy demand in Paris (a comprehensive explanation regarding Paris is presented in Supplementary note 12). The urban heat island (UHI) effect leads to reductions in cost in certain instances. For example, in Madrid (line A–A in Fig. 7b), the UHI reduces the heating demand in winter, when solar energy generation is low, and increases the cooling demand in summer, when it can be more easily accommodated by using solar photovoltaic (PV) panels, which in turn reduces the NPV in Det-U. In a similar manner, the Det–Ex model considers such extreme events along with typical variations using deterministic models that impose constraints to maintain power supply during extreme events. The model reveals that the influence of heat waves is greater for denser cities, such as Madrid and Athens (D–D in Fig. 7c), that belong to the Mediterranean climate zone. Similarly, a notable increase in cost is observed when moving from Det–U to Det–Ex for Stockholm and Paris (line E–E in Fig. 7d) due to the influence of extreme cold and hot events.

The use of stochastic models (Stoc) helps to quantify the impacts of HPLI scenarios brought about by future climate variations, impacts that the deterministic models do not capture. According to the Stoc model, Paris and Stockholm show a marked increase in cost (categorized as Class A, as shown in F–F and G–G in Fig. 7i and j, respectively). Such a marked increase is not observed for the other cities (Class B: Madrid, Athens, and Belgrade), and there were certain instances where a cost reduction was observed when moving from the Det model to the Stoc model (regions L and M in Fig. 6f and g). Higher flexibility (need to be considered at the early design stage as defined by Ref. [25]) is required to withstand the HPLI scenarios brought about by future climate variations for cities belonging to Class A than for those in Class B, which leads to a notable increase in cost. Our assessment reveals that HPLI scenarios bring many more challenges to Nordic and marine west coast climate zones compared with other areas in Europe.

The compound impact of climate variations and densification

Energy systems in urban areas need to withstand the compound impact of climate change and densification; this compound impact is not considered in current state-of-the-art approaches. Neglecting the compound impact may lead to a performance gap between computed performance indicators and reality. Here we calculated an approximate performance gap by simulating the Pareto solutions obtained for the Det model, while accounting for both future climate variations and densification when calculating energy demand and renewable energy generation. The performance gap brought by the compound impact is presented in Fig. 8 a-c. It shows that cost and GI levels can increase by up to 20% and 80%, respectively, due to the compound impact (Fig. 8a and b) when using the current state-of-the-art approach (Det model). Such a significant increase in cost and GI level can become very challenging. More importantly, the power supply can easily collapse because of the failure to consider the compound impact of urbanization (by considering UCM and densification scenarios) and extreme climate events. Loss of load probability can reach up to 30% during an extreme event across five selected cities (Fig. 8c). Therefore, the compound impact brings increased challenges to the energy systems of these cities.

When comparing the Pareto solutions from the Stoc and Comp models, a marked increase in cost is observed for cities belonging to Class B. Such a significant deviation is not witnessed in Paris and Stockholm. It reveals that a reasonable approximation can be taken solely using Stoc model with HPLI scenarios for both Paris and Stockholm, and these can be further improved by considering both HPLI and LPHI events (for example with the use of stochastic-robust model) without accounting for the impact of the urban climate. This can be further justified by the trivial difference between the Det and Det-U Pareto fronts for both Paris and Stockholm. However, such representation considering the climate alone will not provide an accurate representation for cities belong to Class B. Cities in Class B are closer to the equator and have a longer summer period (especially Athens and Madrid), making them more susceptible to heat waves, which will bring a notable change to the demand profile that cannot be captured solely by using a regional climate model coupled with energy demand quantification. On the other hand, it reflects that cities belong to Class B are more susceptible to the compound impact. Withstanding the fluctuations brought about by future climate variations and urban climate will demand higher flexibility that leads to a higher cost when guaranteeing the climate resilience of energy generation. For example, the NPV increase can be up to 60% (line P–P in Fig. 7g) in Madrid due to the compound impact. Therefore, it can be concluded that certain cities are vulnerable to both future climate variations and urban densification (which belongs to Class B) while the others are more vulnerable to future climate variations (Class A).

Qualitative estimation at the EU scale

Climate resilience of energy infrastructure is vital in densely populated urban centers, since a cascade of failures will have a significant impact on many. In certain cities, the compound impact of urban climate and future climate variations play a major role: when improving the climate resilience of energy infrastructure, urban density is important (Class B). In some others the densification is less important (Class A). As such, urban densification trends can be particularly informative to infer the evolution of climate impacts on urban centers. As shown by the land use efficiency indicator, the logarithmic ratio between population and land use varies in a time span (See Eq. 6 in the Methodology Section) (LUE in Fig. 8d), urbanization trends are not homogeneous across all European cities: some urban centers, especially capital cities in Southern Europe, were already extremely dense in 1990 and expanded claiming land at a higher rate than population growth (LUE>1), maintaining density steady. Some other urban centers rather increased their population by densifying consolidated built-up areas between 1990 and 2015 (0<LUE<1), with growing built-up area per capita: cities belonging to Class A and located in Northern countries show this tendency. The impact of future climate on cities will change according to their morphology evolution. The LUE from 1990 to 2015 for over 1000 urban centers in Europe[26] (Fig. 8) reveals an overall reduction in urban densification for 76% of the centers, with a higher concentration of these in eastern Europe, specifically due to the population decrease (Future evolution for the five cities for 2015 are presented in Supplementary note 14). However, England, the Mediterranean coast of Spain and France, central Europe, and Scandinavia show increased densification. This assessment reveals that special attention regarding HPLI climate events needs to be given to cities in Spain, Italy, and Greece that are densely populated and expanding their built-up areas (Fig. 8d). Special attention also needs to be given to improving the resilience of energy infrastructure allowing for the compound impact of extreme climate events and urbanization. The impact on eastern Europe is trivial as many cities are experiencing a reduction in urban density. Rapid urbanization in the UK and central Europe will not intensify the impact of extreme climate events, but if their rapid densification continues, such stability may be compromised, especially in exceptional events. The impact of future climate variations and extreme events will lead to a considerable deviation in renewable energy integration potential obtained from the Comp model across Europe. However, many cities demonstrate the capability to integrate renewable energy to a penetration level close to, or above, that required to achieve net zero or net positive energy districts (Fig. 8d). Nonetheless, HPLI climate events will bring many challenges to reliable energy operation, and renewable energy integration may need to be performed cautiously. We conclude that an optimistic picture regarding renewable energy integration can be seen for many cities in Europe, allowing them to reach 2050 EU targets comfortably. However, the compound impact of future climate variations and urban densification will markedly increase the cost of the energy transition, especially for certain parts of Europe.

Conclusions

Urban areas are experiencing a rapid transformation, becoming both economic hubs and accommodating more varied activities, leading to a notable increase in population size and energy demand. Compactness in urban areas helps to improve resource efficiency. Nonetheless, increasing urban densities will lead to an increase in urban heat island intensity, potentially further enhancing any warming impact of future climate change.

This study shows that future climate variations and extreme events can have a notable impact on ambient temperature, wind speed, and solar irradiation, which leads to a marked variation in energy demand and renewable energy generation, especially when considered at high temporal resolution. Future climate variations and extreme events are further amplified by dense urban morphology. For example, the average cooling demand for Madrid increases by up to 28% via the urban heat island effect. The impact of an urban heat island not only can lead to an increase in cooling demand in summer, but also can reduce heating demand during winter; this pattern of demand may coincide with patterns of solar energy generation, especially in climate zones that have ample solar energy potential. As a result, urban densification leads to a reduction in the cost of energy infrastructure in both Mediterranean and marine west coast climate zones. Improving the resilience of energy infrastructure to extreme climate events and fluctuations in demand and generation brought about by seasonal variability diminishes the advantage (pattern of demand being coinciding with patterns of solar energy generation) while markedly increasing the cost. A considerable performance gap results from the compound impact of future climate variations and urban densification, which leads to an increase in the cost of up to 60% in certain instances, while also creating an increased threat of power supply outages (e.g., up to a 30% increase in blackout risk). The compound impact of increased urban density and future climate variations bring serious challenges when attempting to improve the energy sustainability of cities, especially in the Mediterranean and marine west coast climate zones where urban areas are growing at a considerable pace. The study demonstrates that urban density under different climate conditions can impact urban heat islands which will increase the vulnerability of the power grid. Although, the densification of urban area tends to decrease the cost of capacity expansion, it, however, increases the vulnerability to extreme events as measured by cost, regional dependencies and loss of load probabilities. This is especially observed for cities in the Mediterranean and marine west coast climate. The study reveals that climate change and demand for improve sustainability and resilience of energy infrastructure will challenge global phenominas such as urbanization. Therefore, it is recommended that future research includes the synergies between urban density and climate change in urban energy forecasting during urban planning and grid reliability studies. It is important to invest in the climate resilience of energy infrastructure, while also improving sustainability, if the present economic growth can sustain.

Methodology

The set of climate models used in this study provides information regarding energy demand and renewable energy potential at different levels. Current practices in energy system design consider a period of one year when optimizing an energy system. However, evaluating the impact of future climate variation requires an in-depth understanding of climate systems aided by multiple climate models, and scenarios under which the energy system will operate need to be assessed over a longer timeframe (e.g., 30 years). Given that it is challenging to conduct detailed simulations over such long timeframes, a statistical approach is usually presented to develop probabilistic scenarios that represent HPLI and LPHI extreme scenarios. However, none of these approaches consider the detailed physics of a city. It is not possible to conduct extensive computation over long timescales by using an urban climate model (UCM) due to the complex coupling between building stock and urban climate, a feature that is not considered when using a regional climate model (RCM). Therefore, it is not possible to derive probabilistic scenarios as the computation is too demanding. Coupling between the UCM and the building stock shows fluctuations in energy demand and the renewable energy potential in a much more detailed manner. These fluctuations markedly influence the operation cost as well as the lifespan of system components. When moving into an urban microclimate model (UMM), the information provided is further refined, as the model is closely coupled to building stock and also considers the influence of the urban canopy layer. However, the timescale that these models can accommodate is very short. Therefore, such models are only considered when evaluating the influences of extreme events such as heat waves. Thus, a hybrid model including stochastic–robust–deterministic programing was developed here to enable the linking of different parts of the multiscale climate–urban system.

Synthesis of sequences and extreme events

Thirteen sets of 30-year RCM weather data, having an hourly temporal resolution, were used in this study, taking into account five different GCMs under three emission scenarios (Supplementary note 1 and 10). Three groups of representative weather data were synthesized using RCM data and used in the assessment. This group was developed to simulate the energy performance of buildings, including three datasets representing typical (TDY), extreme cold (ECY), and extreme warm (EWY) years. These three datasets comprised months with the most typical, coldest, or warmest temperatures, respectively, among the considered 390 years (thirteen 30-year scenarios), as described by Nik[10] (Supplementary Note 1). The second group of representative weather data was created adopting a similar philosophy for each hour, instead of a month, representing the most typical, highest, and lowest values that are projected by the climate scenarios for each hour, as described by Perera et al.[17] This second group was used in the robust optimization of the energy system and three subgroups were synthesized, based on the hourly distribution of temperature, global solar radiation, and wind speed, respectively. The third group of weather data was constructed to represent the plausible range of variations that are projected by future climate scenarios. In this regard, the percentiles of the climate variables (temperature, global solar radiation, and wind speed) at each time step were assessed considering all the plausible scenarios (390 data points), divided into specific sequences (e.g., three sequences with percentile ranges of 0%–20%, 20%–80% and 80%–100%), then the average values were calculated for each sequence (e.g., 3.5, 7, and 11 °C for a one hour time step and three sequences). These datasets were used to perform stochastic optimization of the energy system, as described by Perera et al.[17] It is important to note that the second and third groups of weather data do not represent the actual physical behavior and variations of the climate system and have been synthesized specifically for energy calculation and assessment purposes.

Archetypes

Archetypes were developed on a base square of 150 x 150 m, in a Level of Detail LOD-1 (i.e., extrusion of building footprints to their height). Each city has its own archetype for the relevant local climate zone (LCZ), based on the following parameters: (a) average height of the buildings; (b) average sky view factor (SVF) in the public space; and (c) ratio of building footprint area to total plan area. Where available, such parameters have been extracted from the literature;[27] in other cases, data were extracted using a custom Python script[28] from open-source data for terrain elevation,[29] buildings footprint,[30] and height,[31] to a vector 3D model.

Once the parameters were acquired, Rhinoceros 3D modeling software[32] and the associated plugin Grasshopper[33] were used to construct the 3D shape of buildings. In particular, the DeCoding Spaces Toolbox for Grasshopper[34] was employed to generate building volumes, by optimizing several variables through the genetic algorithm Wallacei:[35] variables were optimized to meet the input parameters as closely as possible. Variables include parcel area and width, road width, building length and width, and block type (courtyard, line, or isolated); building heights were generated from a random gaussian characterized by the input mean height as the central value. Ladybug Tools[36] for SVF was used to assess fitness with input parameters for each phenotype generated by the genetic algorithm. The resulting archetypes are presented in Supplementary Note 2.

Urban climate and microclimate models

A multiscale urban climate model (UCM) was used to evaluate the impact of future climatic scenarios on energy demand, considering the urban climate. The canopy interface model (CIM)[37] was used to downscale climatic data and acted as an interface between the climate model data and the building energy simulation software. The created archetype models were used as inputs for the CitySim model.[38] For each of the archetypes, specific building physics properties were extracted from the TABULA[39] and LESOSAI[40] software databases. The characteristics of the envelopes chosen corresponded to "multi-family houses." Moreover, a Grasshopper script was used to generate the geometrical input files needed for the CIM. This script computed the average size (length and width) of the obstacles and streets, every 3 m along the vertical axis, in the urban canopy.

Coupling between CitySim and CIM was similar to the procedure proposed by Mauree et al.[41] and Perera et al.[42] An initial CitySim simulation was run to provide input surface temperature boundary conditions and to compute the energy demand based on the standard climatic data. The local meteorological profiles were subsequently computed with the CIM; the computed surfaces temperatures obtained from CitySim, and the regional climate data. Finally, the building energy demand was computed with CitySim using the local climate produced by the CIM. A total of 150 simulations were thus performed for the 18 cities, considering the 3 climatic datasets (extreme cold, extreme warm, and typical) and with and without the urban climate data (Supplementary Note 3).

A multiscale Urban Microclimate Model (UMM) proposed by Javanroodi et al.[43] is also used to downscale climate variables from mesoscale to microscale and generate hourly microclimate using 3D Computational Fluid Dynamics (CFD) simulations. First, two days with extreme cold (Extreme Cold Day or 'ECD') and warm (Extreme Warm Day or 'EWD') weather conditions were selected out of extreme week data for each city. The generated climate data were used as inputs for 240 CFD simulations based on Reynolds-average Navier-Stokes (RANS) solver using a Standard k- ε turbulence model. The CFD solver is thoroughly validated under a similar setup against in-situ measurements.[44,45] Additionally, the anthropogenic heat emission of the buildings is calculated and imposed as a boundary condition on the external surfaces of each building. Finally, energy demand profiles were computed with CitySim using microclimate data to be compared with UCM and Meso results. The technical details of the proposed urban climate and microclimate models are provided in the Support Document (Supplementary Note 4).

The computational model for energy system optimization

Energy system optimization is used to size the components of distributed energy systems, comprising renewable energy technologies, energy storage, and conventional dispatchable energy technologies (Supplementary Note 5). It requires a joint optimization of system design and operation strategy, which makes it more challenging. In the context of the system, operation strategy converts the problem into a simulation-based optimization problem where the operation of the energy system must be considered over a long timescale. Capturing future climate variations demands a lengthy simulation covering a timescale of up to 30 years, which is well beyond the usual performance of energy system optimization models. Similarly, detailed consideration of urban physics using urban climate and urban microclimate models leads to a more accurate demand profile, which may vary markedly from the demand profile obtained using regional climate models. However, such fine scale models of the urban canopy layer are not suitable for lengthy simulations covering several decades, as these are currently performed using regional climate models.

According to Craig et-al. [13], there are three major bottlenecks on linking the climate and energy system models such as:

1) Poor resolution of global climate models
2) A mismatch between climate and energy system variables used
3) Challenges in handling big-data sets and uncertainty in energy system models

Craig et-al. [13] suggest certain ways to handle these limitations, which we have used in the present study as listed below.

1) Aligning spatial and temporal resolution
2) Moving beyond a single time series and capturing the uncertainties

To address 1), we have used multiscale spatiotemporal model coupling, urban micro climate, urban climate and regional/global climate models.

To Address 2), instead of relying on single time series, we consider deterministic, stochastic and robust models which count typical, high probable low impact as well as low probable high impact scenarios being linked to the multiscale Spatial-temporal model. The following sections explain the methodology developed in this study to consider such multiscale climate models along with energy system models.

Outline of the energy system

The energy hub concept, introduced by Geidl et al.,[46] was used in this study. Compared to models such as Ref. [47] energy hub concept has the potential to consider multiple sectors which is vital in assessing the impact of climate change [48,49]. A multi energy system catering for electricity, heating, and cooling demand supported by solar PV, wind, cogeneration (with heat and power), heat pump, and a battery bank linked into the electricity grid was taken to evaluate the impact of future climate variations and extreme events on the urban sector.Grid curtailments were introduced relating to the injection and purchasing of electricity to and from the grid, respectively. A time of use profile replicating a real-time price scheme was used to consider the cost of electricity from the grid. A thermal network, with thermal energy storage, was not considered (Supplementary Note 5).

Decision space

The decision space represents the variables that must be quantified to reach the optimal design of the energy system. Decision space variables were mapped onto the objective space through a life cycle simulation. The uniqueness of our study was the use of three different models when mapping decision space variables onto the objective space. Each model addressed a specific climate phenomenon either at the regional, urban, or urban canyon level, while also representing the impact of future climate variations and urbanization. The same set of decision variables was considered for the stochastic, deterministic, and robust parts of the model, including parameters related to system design (ϵN) as well as operation strategy (ϵL). The decision space (ϵX (NUL)) consisted of both continuous and discrete variables. The selection of energy technologies and capacities were taken as discrete variables, while the operation strategy was modeled using continuous variables.

Mapping decision space variables onto the objective space

Net present value of the system and grid integration level were considered as the objective functions for the optimization. Loss of load probability was set as a constraint in the optimization. Formulation of objective functions for each class was performed separately as presented below.

Stochastic part of the model system:

The stochastic part of the model system shows the influence of HPLI scenarios that may lead to a significant performance gap in the long run and degrade the performance of the system. In this regard, we considered the set of scenarios that captured long-term future variations using a set of regional and global climate models that reflect different climate scenarios. The pool of scenarios corresponds to a set of time series representing energy demand and renewable energy potential (both wind and PV considered separately) with a probability of occurrence as explained earlier. The system design is simulated for 8760 time steps for each scenario.

Deterministic part of the model system:

Urban climate introduces many fluctuations into the energy demand relating to more compact areas of a city. Significant fluctuations in energy demand can markedly reduce the performance of the energy system, hence increasing the operation cost. The extensive computation time required by the urban climate model makes it difficult to consider the impact of all of the climate scenarios obtained from the regional climate model for a 30-year period. Therefore, we used a statistical approach to generate a typical year, which can represent the overall variations over 30 years taking into account all the different climate models, resulting in a deterministic scenario. The deterministic part of the model thus presents the variation in energy demand brought about by the urban climate and its influence on the energy system when formulating the objective functions.

Robust part of the model system:

The robust part of the model considers the LPHI scenarios. Although these events have a low probability of occurring, they can have a considerable impact on the objective functions and power supply reliability, which is considered a constraint. Evaluating the impact of extreme climate events and their local amplification plays a major role in this regard. Accurate quantification of the joint influence of both of these phenomena is important because LPHI scenarios are directly used when evaluating power supply reliability and thus directly influence the robust operation of the energy system and energy security. Towards this objective, a statistical approach was used to quantify the extreme climate conditions using the output from the regional climate model. The urban climate model was used to further quantify the influence of urban density. However, for extreme events, an urban climate model alone cannot fully capture their influence on energy demand. Therefore, an urban microclimate model coupled with an urban climate model can be helpful in this regard; this can include the urban canopy layer and provide more accurate details. However, such a detailed model cannot be used evaluate the influence over a period of one year. Therefore, the urban microclimate model was used to evaluate the increase in energy demand for extreme conditions (two days considered) obtained by the urban climate model. Subsequently, we assumed that the increase in energy demand obtained by the urban microclimate model was applied to the demand profile obtained from the urban climate model throughout the year, which provided a more reasonable safety margin for the energy system.

Formulation of objective functions and constraints

A Pareto optimization was performed considering net present value (NPV) and system autonomy as objective functions. Net present value shows the financial performance of the energy system reflecting the influences of future climate variations and extreme events. It consists of both initial capital investment in the system (ICC), together with fixed (OM_{Fixed}) and variable ($OM_{Variable}$) operation and maintenance costs. The operation strategy of the system influences both fixed and variable operating costs. Therefore, depending upon the formulation (whether stochastic, robust, or deterministic), the objective function values obtained might vary. The NPV was formulated according to Eq. 1.

$$NPV_{Comp} = ICC + \omega_S \Psi_S^{OM} + \omega_D \Psi_D^{OM} + \omega_R \Psi_R^{OM} \tag{1}$$

In this equation, ω_s, ω_R, ω_D and Ψ^{OM} respectively denote the weight associated with the stochastic, robust, deterministic scenarios and the operation and maintenance cost obtained each scenario. Operation and maintenance cost is computed by using Eq. 2 for stochastic scenarios.

$$\Psi_S^{OM} = \sum_{\forall s \in \Omega} \delta_s \left(\sum_{\forall c \in C} (OM_{c,s}^{Fixed} \, CRF_c) + \sum_{\forall h \in H} \sum_{\forall c \in C} PRI^l OM_{c,h,s}^{\text{variable}} \right), \ \forall s \in S, \forall c \in C, \forall h \in H \tag{2}$$

In this equation, OM_{Fixed} considers recurrent annual cash flows (such as the maintenance cost of wind turbines, PV panels, and fuel and operation costs for the cogeneration unit). $OM_{Variable}$ considers the replacement cost for the cogeneration unit and battery banks. Further, c, s, h, CRF, and PRI denote the component of the energy system considered, scenario considered for the stochastic optimization, year, and capital recovery factor and real interest rate respectively. PRI is computed using both interest rates for investment and the local market annual inflation ratio. Finally, δ_s denotes the probability of occurrence for the specific scenario. A similar approach was used to compute Ψ_R^{OM} and Ψ_D^{OM}, which correspond to the operation and maintenance cost for the robust and deterministic scenarios, respectively.

Grid integration shows the dependence of the energy system on the grid. Maintaining a minimum grid integration level is recommended to ensure the stability of the network. Grid integration level was formulated according to Eq. 3, being similar to NPV.

$$GI_{Comp} = \omega_S \Psi_S^{GI} + \omega_D \Psi_D^{GI} + \omega_R \Psi_R^{GI} \tag{3}$$

We used the approach introduced by Perera et al. [51] for grid integration level, as shown in Eq. 4.

$$\Psi_S = \sum_{\forall s \in S} \delta_s \frac{\sum_{\forall t \in T} P_{t,s}^{FG}}{\sum_{\forall t \in T} ELD_{t,s}}, \ \forall t \in T, \forall s \in S \tag{4}$$

In these equations, $ELD_{t,D}$ $P_{t,R}^{FG}$ denotes the electricity demand, Power supply reliability is considered as a constraint in the optimization process.

Finally, the power supply reliability of the system during extreme events was computed using Eq. 5.

$$LOLP-Ex = Max_{s\in\pi}\left(Max_{t\in T}\frac{\sum_{t=t_0}^{t=t+d} LPS_{t,s}}{\sum_{t=t}^{t=t+d} ELD_{t,s}}, 0\right) \tag{5}$$

In Eq. 5, 'd' denotes the time period over which the extreme climate condition is expected to prevail and LPS denotes the loss of power supply. Each city is represented independently as separate energy hub in the present study. The complete formulation for all the scenarios are presented in Supplementary Note 6 and 7. The operators used for the optimization and the implementation of the optimization problem is explained in Supplementary Note 9.

A detailed description about the model validation is presented in Supplementary note 11.

Land Use Efficiency

Land use efficiency was formulated according to Eq. 6, where Urbt and Urbt+n represent the total areal extent of the urbanized land (intended as the built-up surface extent of the human settlement) at an initial reference year t and at a final reference year t+n, respectively, while Popt and Popt+n express the total population of the urban center at an initial reference year t and at a final reference year t+n, respectively; LN refers to the natural logarithm of the ratio. Eq. 6 expresses the calculation of the ratio of land consumption rate to population growth rate, with y being the total time span in years:

$$LUE = \frac{\frac{LN\left(\frac{Urb_{t+n}}{Urb_t}\right)}{y}}{\frac{LN\left(\frac{Pop_{t+n}}{Pop_t}\right)}{y}} \tag{6}$$

In our study, t corresponds to the year 1990, while t+n corresponds to the year 2015, leading to a y of 25 years. Further details can be found in the literature.[46, 47]

Limitations and future work

The present study limits its scope to consider the uncertainties brought about by climate change when considering the compound impact of urban densification and future climate variations. We do not consider the uncertainties brought about by, for example, technology maturity, market fluctuations for renewables and fossil fuels, and equipment usage patterns, which are classified as uncertainties brought about by human systems. Further, the impact of building densification on the electricity demand is not considered. Recent studies have paved paths to address some of these limitations[26,52]. Another limitation is related to uncertainties brought by human thermal sensation and perception that can change building energy system operation and thus energy demand profiles. In the building archetypes used in the CitySim simulations to produce the energy demand profiles, HVAC systems were assumed to be controlled by thermostat cooling and heating setpoints based on indoor dry-bulb temperature. In reality, how humans perceive temperature varies from person to person as well as region to region but there are standard metrics and scales for example heat index and standard effective temperature (SET) to gauge the feels like temperature and thermal perception. Humans use heating and cooling based on the thermal sensation rather than the temperature measured using a thermometer. The heat index considers indoor air dry-bulb temperature and humidity, while the SET has been used in the ASHRAE thermal comfort standard 55 to evaluate indoor thermal comfort which considers six variables including indoor air dry-bulb temperature, humidity, air velocity, mean surface temperature, occupant activity, and clothing level. For commercial buildings where occupants have limited access to adjust thermostats this assumption of HVAC controlled by thermostat setpoints would not lead to much uncertainty; However, for residential buildings where occupants have more control, such influences can be significant at the individual household level. Uncertainties of occupant behaviors and preferred thermal sensation and their potential impacts on the energy demand profiles at the urban energy system level can be a topic of future research.

The present study uses the energy hub model which has been widely used to design distributed energy systems. The transient stability of the system is not considered in the present study. Furthermore, system approach is used to simplify the optimization process where system-of-system is more appropriate. The optimization process limits its scope to optimal dispatch and capacity sizing. Optimal power-flow or grid extensions are not considered. A comprehensive description about the limitations of the model used is presented in Ref. [51]. The model is focused on the urban scale besides looking at the macro scale picture at the national scale as presented in Ref. [50]

Data availability: The raw climate data are available through Coordinated Regional Climate Downscaling Experiment (http://www.cordex.org/). For each of the building simulation models created, specific physical properties (U-values for roof, walls, windows and ground surfaces, and solar heat gain coefficients) for the building envelopes were extracted from the TABULA database (https://episcope.eu/welcome/).The data relevant to the energy and climate models not found in the in Supplementary Notes 1–3 are available from the corresponding author upon reasonable request.

Code availability: The computational code is available from the corresponding author for academic purposes upon reasonable request.

Author Contribution: A.T.D. Perera: Conceptualization, Methodology, Formal analysis for climate and energy system, Writing; Kavan Javanroodi: Methodology, Formal analysis for climate, energy demand, urban climate and microclimate, Writing; Dasaraden Mauree: Conceptualization, Formal analysis for urban climate and energy demand, Writing - Original Draft; Vahid M. Nik: Methodology, Formal analysis for climate, Writing; Pietro Florio: Methodology, Formal analysis for urban data, Writing; Tianzhen Hong: Writing/review; Deliang Chen Conceptualization, Methodology, Writing/review

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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