Into a cooler future with electricity generated from solar photovoltaic

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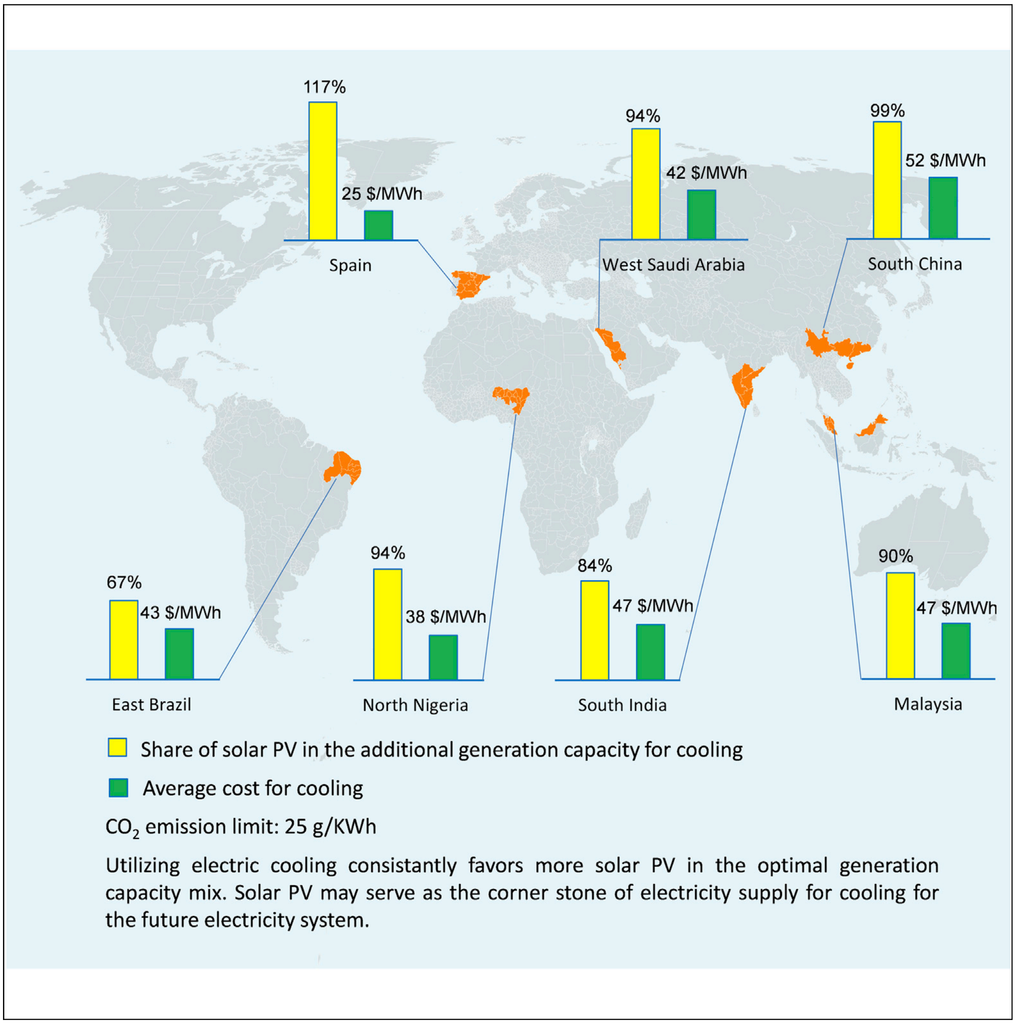

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Highlights

We evaluate the cost-optimal investment in solar PV due to the use of electric cooling

Solar PV is the most competitive generation technology to meet the demand for cooling

Electric cooling may be powered at a lower cost with solar PV than the rest of the demand

Kan et al., iScience 25, 104208
May 20, 2022 © 2022 The Author(s).
https://doi.org/10.1016/j.isci.2022.104208

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Into a cooler future with electricity generated from solar photovoltaic

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SUMMARY

The fast-growing global cooling demand due to income growth in tropical countries necessitates substantial investments in new generation capacity. Despite the synergy between the temporal behavior of cooling demand and solar PV production, it is not clear whether the increased cooling demand will make solar PV more cost-effective or less so. We use a capacity expansion model to investigate the cost-effectiveness of investing in solar PV to meet the electricity demand linked to cooling for seven different regions under various CO_2 emission targets. Solar PV plays a dominant role in meeting the additional electricity demand for cooling, and the share of solar PV in the additional generation capacity ranges from 64% to 135%. Additionally, powering electric cooling with mainly solar PV is cheaper than powering the rest of the demand. These results suggest that solar PV may comprise the backbone of electricity supply for cooling in the future electricity system.

INTRODUCTION

The summer of 2021 witnessed extreme heat waves in both tropical countries and the northern climes. Between 2000 and 2019, around 500,000 deaths per year were associated with too high temperatures globally (Zhao et al., 2021). Sustaining a comfortable temperature for living on hot days is essential for health, well-being, and economic productivity (Salonen et al., 2013; Samet and Spengler, 2003; Vimalanathan and Babu, 2014). Air conditioners (ACs) and electric fans are widely used to keep residences and workplaces cool. In 2016, the global electricity consumption for space cooling was 2,020 TWh, accounting for 10% of the total electricity demand (Birol, 2018). This value is estimated to increase to around 6,500 TWh by year 2050, due to the growth of income and population, and global warming (Birol, 2018; Santamouris, 2016). In terms of regional distribution, the growth of the cooling demand will mainly take place in developing countries located in hot regions, due to increased use of ACs (Birol, 2018; Isaac and Van Vuuren, 2009; Laine et al., 2019). The chief driving force for this growth in demand is the increased wealth in these regions, which enables more people to afford electric cooling through air conditioning. Birol (2018) estimated that by year 2050 the cooling demand would increase 15-fold in India and 13-fold in Indonesia. As a result, the cooling demand would reach around 30% of the annual electricity demand and up to 40% of the peak demand. The increased cooling demand entails investments in new generation capacity (Isaac and Van Vuuren, 2009; Laine et al., 2019). Given the urgent requirement of decarbonizing the electricity system to meet the goal of restricting the global temperature rise to well below 2°C above pre-industrial levels (Edenhofer et al., 2014), the new generation capacity needs to be based primarily on low-carbon technologies such as wind and solar power.

The demand for cooling is typically correlated, both temporally and geographically, with high levels of solar irradiation (Birol, 2018; Isaac and Van Vuuren, 2009; Laine et al., 2019). Similarly, the production of electricity from solar photovoltaic (PV) is mainly driven by the magnitude of solar irradiation, with the output being high when solar irradiation is high. The past decade has witnessed a substantial reduction in the cost of solar PV, and this trend is likely to continue, thanks to technological innovations and the economy of scale (IRENA, 2019a; IRENA, 2020). These preconditions hint at the possibility to use solar energy to power the future cooling demand. Based on such reasoning, (Laine et al., 2019) assumed that the entire future cooling demand would be satisfied with electricity produced by solar PV. In contrast, (Birol, 2018) found that if the electricity system is cost-optimized, not only solar PV but also wind power and a large share of fossil fuel-fired power plants can coexist in the optimal electricity supply mix for cooling. Yet, fossil fuels are not likely to be the solution to the potential large cooling demand, given the goal to decrease anthropogenic carbon

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https://doi.org/10.1016/j.isci.2022.104208

Figure 1. Map of the modeled regions
All of the modeled regions (highlighted in orange) are located in parts of the world with a hot climate.

emissions (Edenhofer et al., 2014). Zhu et al. (2020) evaluated the impact of temperature increase on the sector-coupled energy system in Europe and showed that the temperature increase (higher cooling demand and lower heating demand) leads to higher penetration levels of wind and solar in the optimal electricity supply mix for Europe, and that the wind/solar share remains constant. Given these conflicting results in the literature (Birol, 2018; Laine et al., 2019; Zhu et al., 2020), it is not clear as to whether an increased cooling demand correlates with solar PV becoming more (or less) cost-effective. In addition, we note that the methods adopted in the above studies (Birol, 2018; Laine et al., 2019; Zhu et al., 2020) are not sufficient to tackle this question. Laine et al. (2019) focused exclusively on the cooling sector, without optimizing the investment and the dispatch of the technology portfolio. Birol (2018) did not explore the impact of electric cooling on the investment for a low-carbon electricity system, due to the generous CO_2 emission targets imposed. Zhu et al. (2020) investigated a case with a limited increase in cooling demand and a large decrease in heating demand due to the temperature increase. As a consequence, the results in (Zhu et al., 2020) represent the combined effect of increased cooling and decreased heating.

To perform a comprehensive analysis regarding whether or not adopting electric cooling makes the investment in solar PV more cost-effective in the optimal electricity supply mix, we use a techno-economic cost optimization model (Kan et al., 2020) for capacity investment and dispatch, with representation of solar, wind, hydro, coal, natural gas, storage, and transmission grids (see Method details for the introduction of the model). We explore the future electricity system for seven different regions (see Figure 1 and Table 1) in the tropical and subtropical zones subject to five progressively more stringent CO_2 emission targets.

Table 1. Modeled regions and the residential cooling demand share of the total electricity demand

Region[a]	Size [1000*km^2]	Residential cooling demand percentage of the total electricity demand[b]
Spain	506	3%
South China	845	7%
South India	636	16%
West Saudi Arabia	451	3%
North Nigeria	412	23%
East Brazil	658	17%
Malaysia	330	18%

[a]See Figure 1 for all the modeled regions.
[b]The share of residential cooling demand in the total electricity demand is calculated based on the estimated cooling demand and electricity demand for 2050, see Method details.

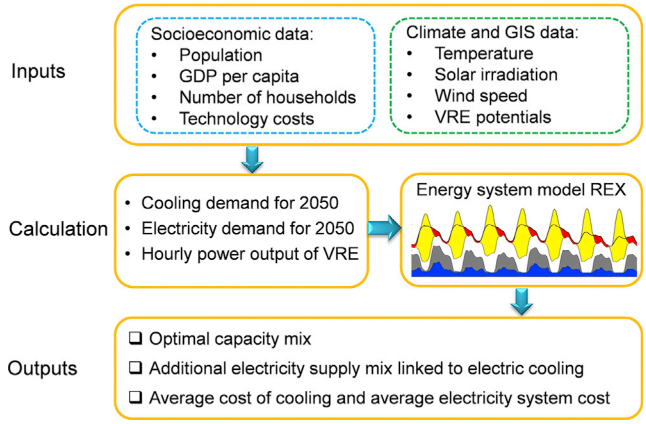

Figure 2. Overview of the method

The text boxes with dashed lines represent the: Socioeconomic data (blue); Climate and GIS data (green). VRE stands for variable renewable energy; GIS stands for Geographic Information Systems.

Specifically, we address two questions with regard to the cost-optimal investments in solar PV to meet the potentially large demand for electric cooling:

1) How does electric cooling affect the cost-optimal investment in solar PV for the future electricity system?
2) How does the CO_2 emission target affect the cost-optimal investment in solar PV due to the adoption of electric cooling?

For each region, the electricity system with and without electric cooling for the residential sector in 2050 is modeled for one year with hourly time resolution. We focus on the residential sector, as most of the increased cooling demand is envisaged to originate from this sector (Birol, 2018; Isaac and Van Vuuren, 2009). By comparing the optimal generation capacity mix for a system with electric cooling to a system without electric cooling, we are able to trace the impact of electric cooling on the cost-optimal investment in solar PV and other electricity generation technologies. Here, we use the term "Case-Cooling" to refer to the system that includes residential cooling, and the term "Case-No cooling" to refer to the system without residential cooling. The additional electricity supply mix due to the provision of residential cooling is obtained by calculating the difference in optimal generation capacity mix between the Case-Cooling and Case-No cooling (see Figure 2 for an overview of the method). The electricity demand for 2050 is estimated using a machine learning approach with consideration of calendar effect, temperature, and GDP (Mattsson et al., 2020). The residential cooling demand in 2050 is projected based on the local climate condition, income level, and energy efficiency of ACs (Isaac and Van Vuuren, 2009; Laine et al., 2019). For more details on how to calculate the electricity demand and cooling demand, see Method details.

We also conduct a sensitivity analysis using different costs for solar, wind, and storage to account for the uncertainties surrounding future technology costs. Three levels of costs are assigned to each of the three technologies: "Low", "Medium", and "High" (see Method details). Varying these three parameters allows us to understand whether the cost-effectiveness of investing in solar PV due to the demand for electric cooling is undermined by expensive solar and storage, or cheap wind power. In the Base scenario, the temperature and the data for VRE (variable renewable energy) resource profiles are based on the values for year 2018. To further understand how the variations in temperature and output of solar and wind on an interannual basis affect the investment in solar PV, four extra weather years (2011, 2014, 2017, and 2019) are selected for the sensitivity analysis.

RESULTS

Impact of electric cooling on solar PV investment

We first evaluate the impact of residential electric cooling on the investment in solar PV. As is apparent from Figure 3, across a wide range of geographic locations and CO_2 emission limits, adding electric cooling

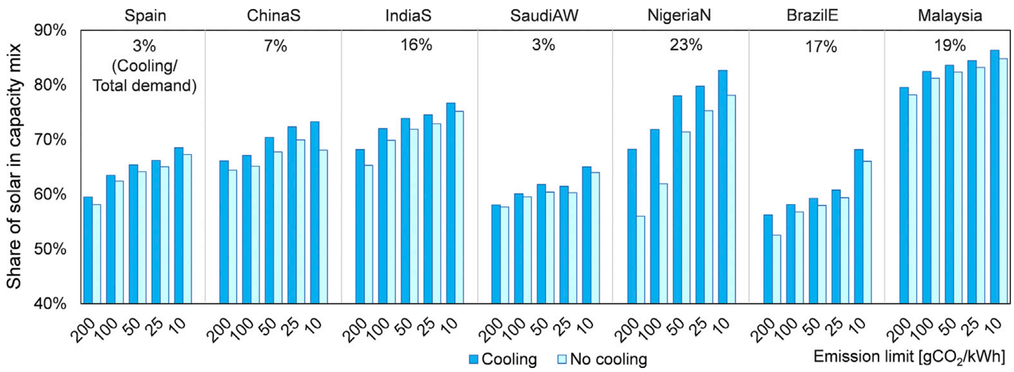

Figure 3. The share of solar PV in the optimal capacity mix for the modeled regions under different carbon emission limits

The percentage listed above the bars is the cooling demand share of the total electricity demand.

(Case-Cooling) consistently increases the share of solar PV in the optimal capacity mix, as compared to the case without electric cooling (Case-No cooling). The exact share increase (absolute percentage change) for solar PV due to electric cooling varies depending on the region and the emission limit. Specifically, the share of solar PV increases by up to 4% for East Brazil (*BrazilE*) and by up to 2% for Spain. The largest increase (12%) is estimated for North Nigeria (*NigeriaN*), possibly because it has the highest cooling demand share (23% of the total electricity demand) among the modeled regions. As expected, the share of solar PV in the optimal capacity mix varies with CO_2 emission limit. Yet, even for a system with a comparably low share of solar PV, adding electric cooling to the demand favors more solar PV in the optimal capacity mix.

Additional electricity supply mix due to cooling

To further understand the change in the optimal capacity mix due to electric cooling, we calculate the change of the optimal capacity mix between Case-Cooling and Case-No cooling. Thus, we are able to analyze which technologies are added to meet the higher demand for Case-Cooling. Figure 4 shows the share of different generation technologies in the total increased generation capacity for Case-Cooling relative to Case-No cooling (the additional electricity supply mix). Despite the wide range of geographic locations and emission limits, the additional electricity supply mix is dominated by solar PV in all the modeled regions. Specifically, the share of solar PV in the additional electricity supply mix ranges from 64% to 135%.

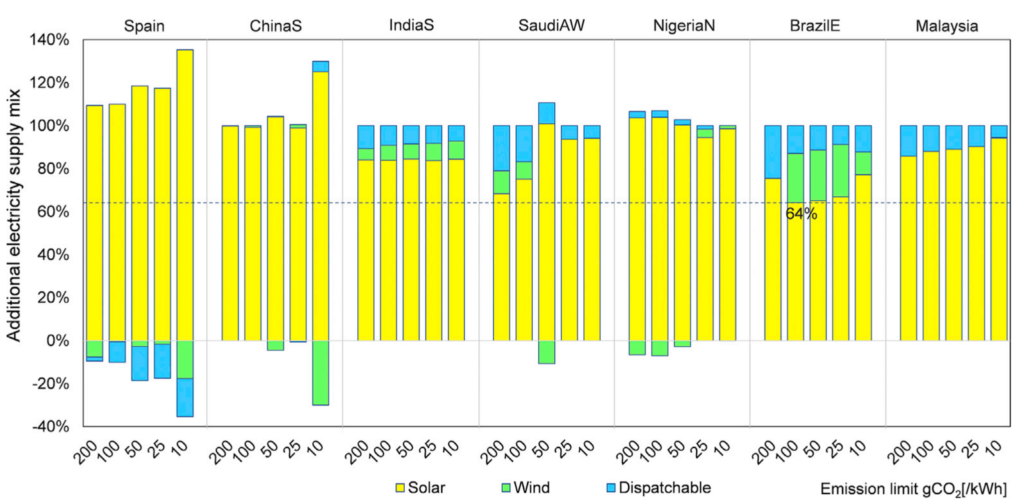

Figure 4. The additional electricity supply mix for Case-Cooling versus Case-No cooling

The additional electricity supply mix is obtained by calculating the change of each generation technology between Case-Cooling and Case-No cooling and then dividing the change by the difference in total generation capacity between the two cases. The positive value represents a capacity increase for the generation technology for Case-Cooling relative to Case-No cooling, while the negative value represents a decrease in capacity for the generation technology.

When the emission limit is at the lowest level (10 gCO_2/kWh), solar PV supplies more than 80% of the additional generation capacity linked to the utilization of electric cooling. This suggests that if there is deep decarbonization of the electricity system, it is cost-effective to invest in solar PV to meet the additional electricity demand entailed by cooling. Note that even with a less stringent emission limit, solar PV persists as the chief generation technology in the additional electricity supply mix. This implies that solar PV is the most competitive generation technology for powering cooling not only in a renewable electricity system but also in a semi-renewable system where fossil fuel-fired power plants are still online. Apart from the prominent role of solar PV, we also observe an increase in battery storage to meet the increased demand linked to cooling at night (see Figures S1 and S2). Battery storage fits well with the diurnal variation of solar PV.

The reason why the share of solar PV exceeds 100% for some scenarios is that the change in the electricity demand profile due to cooling enables solar PV to replace other generation technologies that exist in the optimal capacity mix for Case-No cooling. This is confirmed by the decrease in the shares of wind and dispatchable power in the additional electricity supply mix (see Figure 4). All these findings indicate that adding electric cooling can change the demand profile in such a way that solar PV becomes more cost-effective also for the other part of the electricity demand. In addition to the prominent role of solar PV, both dispatchable and wind power are present in the additional electricity supply mix. For instance, in South India (*IndiaS*) and *BrazilE*, additional wind power is installed for Case-Cooling, although the share of wind in the additional electricity supply mix is lower than the share of solar PV.

To elucidate why the additional electricity supply mix linked to cooling is dominated by solar PV, we investigate the correlation between the hourly cooling demand and the hourly output from solar PV and wind power during the summer period when the cooling demand is high. Figure 5 shows the results for two

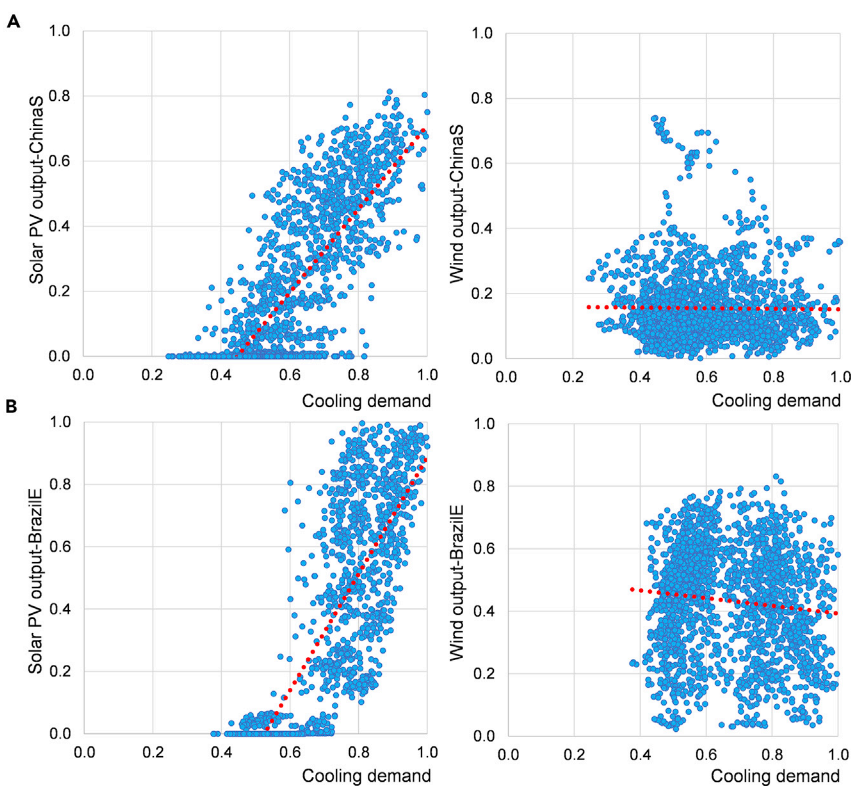

Figure 5. Correlation between the hourly cooling demand and the hourly output from solar PV and wind power during the summer period for: (A) *ChinaS*; and (B) *BrazilE*

The *x* axis represents the hourly cooling demand normalized to the yearly maximum cooling demand. The *y* axis represents the hourly output from solar PV (or wind power) normalized to the installed capacity. The red dashed line is the trend line.

regions with typical cooling demand patterns: South China (*ChinaS*) and *BrazilE*. For *ChinaS*, the cooling demand is mainly concentrated in the summer period, while in *BrazilE*, cooling demand is stable year-round. For both regions, the time series of the cooling demand is positively correlated with the output of solar PV, and the corresponding Pearson correlation coefficients are 0.81 for *ChinaS* and 0.84 for *BrazilE*. This result holds true for all the other modeled regions, with the correlation coefficient ranging from 0.70 to 0.84 (see Figures S4, S5, S6, S7, and S8). Therefore, the time series of the cooling demand coincides well with the output of solar PV, and this apparent synergy incentivizes the installment of solar PV when electric cooling is utilized. As a result, the additional electricity supply mix is mainly covered by solar PV and the share of solar PV in the optimal capacity mix for Case-cooling is greater than that for Case-No cooling. In comparison, the correlation coefficient between cooling demand and wind power output is 0 for *ChinaS* and −0.1 for *BrazilE*, which explains the limited share of wind power in the additional electricity supply mix.

Average cost of cooling and average electricity system cost

The average cost of cooling and the average electricity system cost are depicted in Figure 6. The average cost of cooling is obtained by calculating the difference in electricity system cost between Case-Cooling and Case-No cooling and dividing it by the electric cooling demand. The average electricity system cost for Case-No cooling represents the average cost of all the demand other than the demand for cooling. As is apparent from Figure 6, the average cost of cooling is lower than or comparable to the average cost of all the demand other than that for cooling. The largest cost difference is observed for Spain, where the average cost of cooling is around half of the average cost for the rest of the demand. This means that the cost of covering cooling demand is, if anything, lower than that of covering the remainder of the demand.

The average cost of cooling for the seven regions lies in the range of 24–52 $/MWh, while the average electricity system cost falls in the range of 40–65 $/MWh. The average electricity system cost is lower for Case-Cooling than for Case-No cooling for most of the regions, with the exception of West Saudi Arabia (*SaudiAW*). For *SaudiAW*, the average electricity system cost increases by less than 1%. The share of cooling demand in the total electricity demand varies from 3% to 23% for the modeled regions. Despite such a large variation in cooling demand, adding electric cooling to the demand does not escalate the average electricity system cost.

Sensitivity analysis

Technology costs

We also run the model under different costs for solar, wind, and storage. Despite the large range of technology cost assumptions, adding electric cooling to the demand consistently favors investments in solar PV. As is shown in Figure S9, the share of solar PV in the optimal capacity mix is clearly larger for Case-Cooling than for Case-No cooling in almost all the modeled cost sensitivity scenarios. An exception

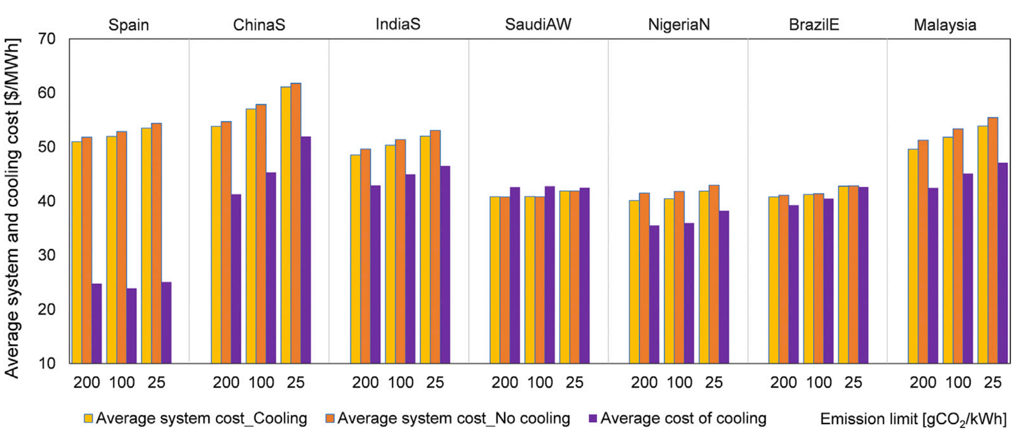

Figure 6. The average electricity system cost and the average cost of cooling

The average electricity system cost is obtained by dividing the total electricity system cost by the total electricity demand. The average cost of cooling is calculated by dividing the difference in electricity system cost between Case-Cooling and Case-No cooling by the electric cooling demand. For the sake of simplicity, we only show the results obtained under three emission limits.

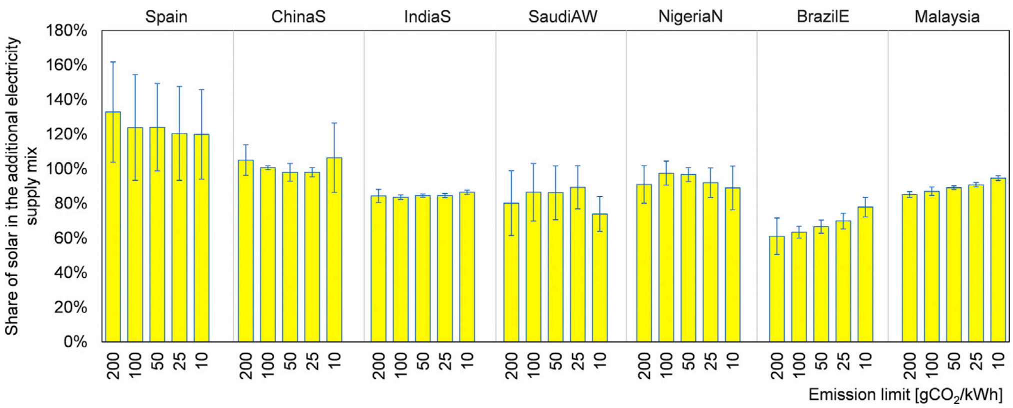

Figure 7. The share of solar PV in the additional electricity supply mix under different cost assumptions for wind, solar, and storage

The yellow column represents the average share of solar PV in the additional electricity supply mix. The error bar represents the standard deviations of the results in different scenarios.

is the scenario of low storage cost for *SaudiAW*, where the share of solar PV is almost identical for both Case-Cooling and Case-No cooling. Compared with the Base scenario, the share of solar PV in the optimal capacity mix differs with the technology cost assumptions. Specifically, the share of solar PV is larger for a lower cost for solar power and storage or a higher wind power cost. Despite the evident change in the share of solar PV in the optimal capacity mix due to different technology costs, adding electric cooling to the demand always favors the addition of solar PV.

The additional electricity supply linked to cooling is mainly covered by solar PV (see Figure 7). Even with low-cost projections for wind power or high-cost assumptions for solar power and storage, the additional electricity supply due to the adoption of electric cooling is still dominated by solar PV (>46%). It is well established in the literature that a low cost for wind or a high cost for solar and storage may suppress the investment in solar PV for a highly renewable electricity system (Kan et al., 2020; Reichenberg et al., 2018; Schlachtberger et al., 2017, 2018). However, our results show that varying these costs does not alter the prominent role of solar PV in supplying electricity to meet the increased demand due to cooling in the future electricity system.

Figure 8 shows how wind, solar, and storage costs affect the average cost of cooling. The average cost of cooling lies in the range of 20–63 $/MWh. As expected, higher investment costs for solar power and storage yield a higher cost to cover the cooling demand. Conversely, a lower cost for solar power or storage consistently reduces the cost of cooling, while the cost of wind power has a minor impact on the cost of cooling. Similar to the findings for the Base scenario, the average cost of cooling is lower than or comparable to the average cost of all the demand other than that for cooling (see Figure S10).

Different weather years

Figure S11 shows the additional electricity supply mix for the sensitivity analysis of four different weather years (2011, 2014, 2017, and 2019), in addition to the Base scenario year of 2018. The share of solar PV in the additional electricity supply mix ranges from 55% to 130% for the seven regions, which differs by less than 9% from the Base scenario. Solar PV remains the most competitive generation technology in the additional electricity supply mix, even under different, annually fluctuating weather conditions. As is depicted in Figure S12, the average cost of cooling for the seven regions lies in the range of 22–56 $/MWh, which differs by less than 8% from the Base scenario. The average system cost decreases for most of the regions when electric cooling forms part of the demand, which is consistent with the result for the Base scenario. Therefore, it is clear that varying the weather year as input to the model has a minor impact on the main outcomes of this study.

DISCUSSION

The emerging demand for electric cooling in developing countries in hot climate regions necessitates substantial investments in new generation capacity. Through investigating the impacts of electric cooling

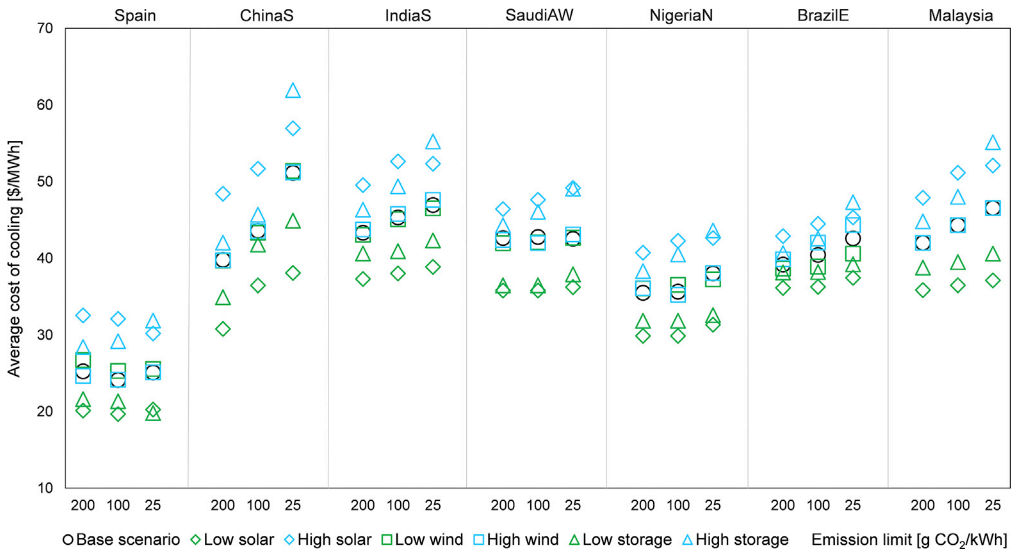

Figure 8. The average cost of cooling under different cost assumptions for wind, solar, and storage

on the optimal capacity mix, we find that it is more cost-effective to invest in solar PV for the system with cooling relative to the one without cooling. This is mainly due to the high degree to which the time series of the cooling demand matches the output of solar PV. Both the demand for cooling and the output of solar PV are largely driven by solar irradiation. Thus, it is the positive correlation between the cooling demand and the output of solar PV that incentivizes investments in solar PV. (Laine et al., 2019) showed that regions closer to the equator exhibit a stronger synergy between cooling and PV. Similarly, we observe a higher correlation coefficient between the annual time series of the cooling demand and PV production for regions closer to the equator. Our results show that the investment in solar PV is not only determined by the synergy between cooling and PV but is also influenced by the availability of other competitive electricity generation resources, although the former plays a more important role. Birol (2018) calculated the additional electricity generation capacity needed to meet the future cooling demand and showed that both VRE and a large share of fossil fuel-fired power plants coexist in the additional electricity supply mix for cooling. By way of comparison, in the present study, the additional electricity supply mix linked to cooling is dominated by solar PV. Our study has more solar PV, possibly due to the more stringent CO_2 emission limits in force. Zhu et al. (2020) found that increasing the temperature (higher cooling demand and lower heating demand) for Europe favors both wind and solar PV generation. In the present study, adding electric cooling to the demand leads to greater investment in solar PV than in wind power. A possible explanation for the discrepancy between our results and those of (Zhu et al., 2020) is that they investigated a case with a minor increase in the cooling demand and a major decrease in the heating demand. The impact of increased cooling demand on the cost-optimal investment in solar PV might be affected by the large decrease in heating demand. In addition, (Zhu et al., 2020) found that a higher temperature favors more solar PV (than wind) in southern Europe, where the increase in cooling demand is more evident than in Europe as a whole. Similarly, (Kan et al., 2021) found that if the electricity demand profile displays a higher summer peak (e.g., due to the greater need for cooling), more solar PV is installed in the electricity system. The results reported by other studies (Zhu et al., 2020; Kan et al., 2021) are consistent with our findings regarding the impact of adopting electric cooling on the cost-optimal investment in solar PV.

Notwithstanding the large uncertainties surrounding technology costs, a robust finding from the sensitivity analysis is that solar PV comprises the backbone of the additional electricity supply mix for the increased demand due to the adoption of electric cooling. Solar PV accounts for half or more of the additional electricity supply mix for both stringent and relatively generous carbon emission targets. In addition, the change in electricity demand profile due to the inclusion of electric cooling may even contribute to solar PV becoming more cost-effective for the rest of the electricity demand. All these findings suggest that adding electric cooling to the demand, to an evidently noteworthy degree, benefits investments in solar PV.

The dominant role of solar PV in supplying electricity for cooling also under a relatively generous emission target indicates the cost-competitiveness of solar PV, as compared to generation technologies that are based on fossil fuels in a semi-renewable electricity system (see Figure 4). Currently, most tropical countries rely heavily on fossil fuels for electricity supply (IEA, 2020). With these countries becoming wealthier and, thereby, gaining greater access to electric cooling, solar PV may serve as a cost-effective option to power the emerging cooling demand, thanks to the substantial reduction in cost for solar PV. The beneficial synergy between cooling demand and investment in solar PV may enable tropical countries to initiate the process of decarbonization of the electricity system at an early stage, rather than following a later path toward decarbonization.

For most of the modeled regions in this study, adding electric cooling decreases the average electricity system cost. The average cost of cooling for the seven regions lies in the range of 24–52 $/MWh, which is lower than or similar to the average cost of all the demand other than that for cooling. These results may seem counterintuitive, as the experience grained with a power system based on thermal power plants may have instilled the notion that the increase in peak demand (due to electric cooling) precipitates a need for peaking power plants. As these plants have lower utilization times and higher running costs than base-load plants, they entail a higher system cost. Yet, here we show that the rule of thumb to avoid peaks in demand in order to decrease costs no longer holds true when adding electric cooling to a system that has a high penetration level of solar PV. The lower cost for cooling is a result of the change in the intertemporal electricity demand pattern. With the increased use of electric cooling, the demand profile displays a variation that is better correlated with the variation in solar PV production, which leads to a high utilization rate for solar PV. Thanks to the long utilization time and zero running cost for solar PV, the average electricity system cost decreases when solar PV is installed to meet the increased electricity demand due to cooling. Taken together, this indicates that solar PV could be a suitable solution to sustain a comfortable indoor temperature condition in countries with hot climates.

Limitations of the study

In this study, we did not explicitly investigate the impact of climate change on the investment in solar PV. With the impact of climate change, the global mean temperate will increase, which may entail a larger cooling demand in the modeled regions. Yet, our study covers seven regions with a wide range of cooling demands, and our results are consistent for all the regions (with various shares of cooling demand in the system). Therefore, climate change is not likely to affect our main conclusion regarding the investment in solar PV due to the adoption of electric cooling. We focused on small regions with comparable sizes rather than the whole country or the entire continent. By doing so, we are able to better reveal the impact of electric cooling on the local cost-optimal investment in solar PV. This is mainly because in an interconnected electricity system, the optimal investments in generation capacity for one region are usually affected by the level of demand and resource availability in the other regions (Reichenberg et al., 2018; Schlachtberger et al., 2017). We do see that isolating these regions may underestimate the contribution of electricity trade to meet the emerging cooling demand.

Note that we did not model with realism the evolution of the electricity system due to electric cooling for each region, and thus, our results do not reflect the cost of transitioning from the current fleet to the future system. Instead, we used a Greenfield approach to investigate the general impact on the investment of solar PV from electric cooling. We did investigate scenarios with relatively generous CO_2 emission targets. With generous CO_2 emission targets in force, more coal and natural gas power plants can be installed, which reflects somehow the contribution of existing fossil fuel power plants in meeting the electricity demand. Still, our results show that even for a system with a relatively large share of fossil fuel power plants, the increased cooling demand is mainly covered by newly installed solar PV.

Another limitation for this study is that the residential cooling demand is estimated mainly on temperature and income while other factors such as building occupancy and building structures are neglected. For instance, the cooling demand is high during late evening hours when people are about to sleep in buildings made of bricks and cement, which have a big thermal mass (Balaras, 1996). Therefore, the method used for estimating cooling demand in this study may underestimate the cooling demand in the evening when there is no output from solar PV, which may overestimate the contribution from solar PV in covering the emerging cooling demand. We anticipate that future studies with a better representation of cooling demand in the evening will confirm or reject the universality of some of the conclusions drawn in this paper.

Conclusion

In this paper, we evaluate the cost-optimal investment in solar PV due to the adoption of electric cooling for seven different regions with various electric cooling demands and different solar and wind conditions. We show that solar PV is the most cost-optimal generation technology for meeting the increased electricity demand from cooling, thanks to the positive correlation between the time series of the cooling demand and the solar PV output. The share of solar PV in the additional electricity supply for cooling ranges from 64% to 135% across the seven regions. The dominant role of solar PV in powering electric cooling holds true for a wide range of carbon emission targets and cost assumptions, and for different weather years. Moreover, we show that electric cooling can be powered at a cost that is lower (by up to 50%) than the cost for the remainder of the electricity demand. These results indicate that solar PV can serve as the cornerstone of the electricity supply for cooling in the future electricity system.

With the developing countries in the tropical zones becoming wealthier, as well as the expected temperature rise due to global warming, electric cooling will be widely adopted to sustain comfortable indoor temperatures. Our results show that solar PV may serve as a cost-optimal option to power the emerging cooling demand not only for a renewable electricity system, but also for a semi-renewable system in which fossil fuel-based power plants are still in commission. This implies that it is cost-optimal to expand solar PV generation concomitantly with the increased use of electric cooling. Because most of these countries rely heavily on fossil fuels for electricity generation, powering electric cooling with solar PV could contribute to earlier decarbonization of the electricity system for these countries.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- KEY RESOURCES TABLE
- RESOURCE AVAILABILITY
  - Lead contact
  - Materials availability
  - Data and code availability
- METHOD DETAILS
  - Model introduction
  - Electricity demand and residential cooling demand
  - Other input data

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2022.104208.

ACKNOWLEDGMENTS

The authors thank Christian Fleischer, Maruf Md Nasimul Islam, Emil Nyholm, and Johan Dahlberg for helpful discussions and suggestions. This work was conducted as part of the ENSYSTRA project, which was supported by the European Union's Horizon 2020 research and innovation program under the Marie Skłodowska-Curie grant agreement No: 765515.

AUTHOR CONTRIBUTIONS

Conceptualization, X.K., F.H., and L.R.; Methodology, X.K., F.H., L.R., and O.H.; Formal analysis, X.K.; Writing – original draft, X.K.; Writing – review & editing, X.K., F.H., and L.R.; Supervision, F.H., L.R., and O.H.

DECLARATION OF INTERESTS

The authors declare no competing interests.

Received: November 29, 2021
Revised: March 28, 2022
Accepted: April 4, 2022
Published: May 20, 2022

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Electricity demand, GDP, temperature, wind and solar data	(Mattsson et al., 2020)	https://github.com/niclasmattsson/GlobalEnergyGIS
Experimental models		
Energy system model REX	(Kan et al., 2020)	https://doi.org/10.5281/zenodo.6110032
Residential cooling demand model	(Isaac and Van Vuuren, 2009)	https://doi.org/10.1016/j.enpol.2008.09.051
Software and algorithms		
Julia	https://julialang.org/	1.4.2
Gurobi	https://www.gurobi.com/	8.1.1

RESOURCE AVAILABILITY

Lead contact

Please contact the lead contact, Xiaoming Kan (kanx@chalmers.se) for further information regarding the data and code used for this study.

Materials availability

This study did not generate new unique materials.

Data and code availability

The model-specific code, input data, and output data are available online to further enhance the transparency and reproducibility of the results (Kan et al., 2022a).

METHOD DETAILS

Model introduction

In this study, seven regions with potentially high levels of demand for residential air-conditioning are investigated using the REX model (Kan et al., 2020). The REX model is a Greenfield techno-economic cost optimization model that handles capacity investments and the dispatch of electricity generation, transmission, and storage. The model applies an overnight investment approach to identify the minimum cost portfolio for the future electricity system given the constraints of meeting the electricity demand, the renewable energy resource potentials, and a CO_2 emission limit. The model, the generation technology options, and the variation management strategies are summarized in Figure S13.

The nodes in the model are labeled by r, the electricity generation technologies at the node are represented by n, and t is the time of the year. The total annual system cost consists of fixed annualized costs C_n for electricity generation capacity G_{rn}, fixed annualized costs $C^{storage}$ for storage S_r, fixed annualized costs $C_{rr'}$ for transmission capacity $Z_{rr'}$ and variable costs R_n for electricity generation g_{rnt}. For storage and transmission, the variable cost is assumed to be zero. Therefore, the objective function of this linear optimization problem is formulated as follows:

$$Min \sum_{r,\,n} C_n G_{rn} + \sum_{r} C^{storage} S_r + \sum_{r,\,r'} 0.5 C_{rr'} Z_{rr'} + \sum_{r,\,n,\,t} R_n g_{rnt}. \qquad \text{(Equation 1)}$$

Since $Z_{rr'}$ and $Z_{r'r}$ represent the capacity for the same transmission line rr', a coefficient of 0.5 is incorporated into the transmission cost formula to avoid double counting.

The electricity demand has to be satisfied through generation, trade and storage.

$$\sum_n g_{rnt} + \sum_{r'} \left(\eta_\gamma \gamma_{r'rt} - \gamma_{rr't}\right) + \left(\eta_s \alpha_{rt} - \beta_{rt}\right) \geq D_{rt} , \quad \text{(Equation 2)}$$

where g_{rnt} is the electricity generation, $\gamma_{rr't}$ is the electricity traded from node r to node r', η_γ is the efficiency of transmission, α_{rt} is the discharge from storage, β_{rt} is the charge into storage, η_s is the round-trip efficiency of storage and D_{rt} is the hourly electricity demand.

For the other constraints imposed on the optimization problem and a more detailed description of the model, see (Kan et al., 2020). The cost assumptions for key technologies and other input data are listed in the below tables.

Electricity demand and residential cooling demand

The total electricity demand, as well as the hourly demand profile, for each region is projected based on the approach developed by (Mattsson et al., 2020). The hourly demand profile is estimated based on a machine learning approach. It applies historical demand profiles for 44 countries and fits them to a gradient boosting regression model (Friedman, 2001), so as to calculate the hourly demand series. The regression variables consist of calendar effects (e.g., hour of day, weekday and weekend), temperature (e.g., hourly temperature in the most populated areas of each region), and economic indicators (e.g., local GDP per capita). Note that apart from the variables described here, the machine learning approach does capture the features (such as the use of ACs) from typically rich and hot countries when creating synthetic demand for other countries that have similar variables. The hourly demand profile is then scaled to match the annual electricity consumption for each region in Year 2050. The annual electricity consumption in 2050 is estimated by extrapolating the annual demand in Year 2016 (IEA, 2020) using the regional demand growth between 2016 and 2050 in the Shared Socioeconomic Pathway 2 (SSP2) scenario (Riahi et al., 2017). For more details on how to produce the synthetic electricity demand, see (Mattsson et al., 2020).

The annual electricity demand for residential cooling in each region is calculated based on the method of (Isaac and Van Vuuren, 2009) and (Laine et al., 2019). The electricity consumption for each household and the fraction of households using ACs (penetration) are assumed to be dependent upon income level and local climate conditions. This assumption reflects the fact that household electricity consumption for cooling and the penetration level of ACs are generally higher in warmer and richer regions. Therefore, the annual electricity consumption for cooling in each region, E, is decided by the local population, GDP, number of households, hourly temperature, and energy efficiency for ACs. E is formulated as:

$$E = N \times A \times S_{\max} \times e / \eta \quad \text{(Equation 3)}$$

where N is the number of households in each region, A (availability) is the share of households that can afford air-conditioning, S_{max} (climate maximum saturation) is the fraction of households that would use ACs if they could afford them, e is the annual cooling demand for each household with air-conditioning, and η is the energy efficiency factor for ACs. A and S_{max} together determine the penetration level of ACs.

S_{max} and e are both influenced by a climate-related parameter, the cooling degree days, CDD:

$$\text{If } T_m(t) > T_{base},\ CDD(t) = T_m(t) - T_{base},\ CDD(t) = 0, \quad \text{(Equation 4)}$$

where $T_m(t)$ is the daily mean temperature for day t, and the base temperature T_{base} is 18°C (Isaac and Van Vuuren, 2009).

S_{max} is decided by the annual cooling degree days, CDD_a, which reflects how hot the temperature is on an annual basis for each region:

$$S_{\max} = 1 - 0.949 \times \exp(-0.00187 \times CDD_a). \quad \text{(Equation 5)}$$

A is dependent upon the income of the population, which is measured in GDP per capita:

$$A = 1 / \left(1 + \exp\left(-0.304 / 1000 \times GDP / cap + 4.152\right)\right). \quad \text{(Equation 6)}$$

The cooling demand for each household, e, is decided by the local climate condition and income level:

$$e = CDD_a \times \left(0.865 \times \ln GDP / cap - 5.825\right). \quad \text{(Equation 7)}$$

Note that the GDP per capita input is in the form of purchasing power parity (PPP), in US 2005 dollars.

The hourly cooling demand is calculated with the cooling degree hour (CDH) and it is assumed to be directly proportional to the CDH (Zhu et al., 2020).

$$\text{If } T(i) > T_{base}, \; CDH(i) = T(i) - T_{base}, \; \text{else } CDH(i) = 0, \qquad \text{(Equation 8)}$$

where $T(i)$ is the ambient temperature for hour i in one day. The time series of the cooling demand is then scaled according to the annual cooling demand for each region, as calculated by Equation (3).

The share of residential cooling demand in the total electricity demand for each region is then calculated by dividing the estimated residential cooling demand by the synthetic electricity demand for 2050.

Other input data

The number of households for each country in Year 2050 is produced by extrapolating the value from Year 2020 (Euromonitor, 2020) using the average household growth rate projected in a previous publication (Un-Habitat, 2013). The number of households in each modeled region is proportional to the regional population share in the country. The data for population, GDP, hydropower, temperature, wind and solar are all obtained using the GlobalEnergyGIS model developed by (Mattsson et al., 2020). The population and GDP for Year 2050 are estimated based on the SSP2 scenario, which represents the middle development path wherein social, economic, and technologic trends do not shift markedly from their historical patterns (O'Neill et al., 2014; Riahi et al., 2017). The energy efficiency factor for ACs is 3.5 for Year 2050 (Rong et al., 2007).

The seven regions modeled in this study are located in the hot climate zones with evident demand for electric cooling. These regions have comparable geographic sizes, and their shares of cooling demand in the total electricity demand lie in the range of 3%–23% (see Table 1), which allows us to evaluate whether the specific share of cooling demand in the total electricity demand would affect the cost-optimal investment in solar PV. Each region is divided into several subregions, which are assumed to be connected with high-voltage direct current (HVDC) transmission grids. The length of the transmission line is measured as the distance between the population center of each subregion (Mattsson et al., 2020) (see Figure S14). The electricity trade is represented as a simple transport problem (Schlachtberger et al., 2017, 2018), and all the subregions in the model are treated as "copper plates" without intraregional transmission constraints. The cost of 4-h lithium-ion battery is used as a reference for storage in the model (Cole and Frazier, 2019).

The modeled subregions are divided into pixels (0.01° × 0.01°) (Kan et al., 2022b). The hourly temperature of the largest population center in each subregion is adopted as the regional temperature time series. The wind and solar technologies are divided into five classes based on resource quality, so as to represent more accurately the capacity factors for wind and solar power (Mattsson et al., 2020). The hourly capacity factor for solar is calculated based on solar irradiation, assuming that the PV technology is fixed-latitude-tilted. The capacity factor for wind is estimated based on wind speed and on the power curve for a typical wind farm equipped with Vestas 112 3.075 MW wind turbines. The solar irradiation and wind speed data are obtained from the ECMWF ERA5 database (ECMWF) and Global Wind Atlas (Badger et al., 2021). The available land is given as a percentage of the suitable land, i.e., the total land area minus the areas that are not suitable for large-scale wind and solar power plants, e.g., protected areas, see below table. Specifically, utility-scale solar unit may be placed on all land types, with the exception of forests; solar rooftop may be placed in urban areas; onshore wind may be placed on all land types, although areas with a population density >500 people per km^2 are excluded; and offshore wind may be placed at sea where the depth is less than or equal to 40 m. All the data for temperature and the VRE profiles are based on the values for Year 2018.

Assumptions made regarding the capacity limits of wind and solar PV

	Solar PV	Solar Rooftop	Onshore wind	Offshore wind
Density [W/m^2][a]	45	45	5	8
Available land [%]	5%[b]	5%	8%	33%

[a]The term "Density" refers to the capacity assumed to be installed per unit area for a typical solar or wind farm. The available land is listed as a percentage of the suitable land.
[b]Owing to the low availability of suitable land in some regions, 1% of the forest area is allowed for the installation of solar PV.

The data for hydropower capacity and hydro reservoir size are obtained based on (Mattsson et al., 2020). The hydropower capacity is maintained at the current level due to environmental regulations. To satisfy the downstream ecosystem and human needs for water, 5% of the mean annual inflow is set as the minimum environmental flow (Efstratiadis et al., 2014; Renofalt et al., 2010) for the hydro reservoirs. In terms of CO_2 emission targets, five progressively more stringent emissions limits, from 200 down to 10 gCO_2/kWh, are applied in this study. This is equivalent to 62% to 98% reduction in CO_2 emission per kWh of electricity generated, as compared with the global average emission level in Year 1990. The cost data for the main technologies for Year 2050 are summarized in below table. These data are taken primarily from a recent report (Akar et al., 2020). The investment cost is then converted to the annualized cost, using a discount rate of 7%. The detailed cost assumptions for the sensitivity analysis are listed in below table.

Cost data and technical parameters

Technology	Investment cost [$/kW]	Variable O&M costs [$/MWh]	Fixed O&M costs [$/kW/yr]	Fuel costs [$/MWh fuel]	Lifetime [years]	Efficiency/Round-trip efficiency
Natural gas OCGT	524[a]	4	11	36	30	0.35
Natural gas CCGT	913	2	13	36	30	0.6
Coal[b]	1300	4	40	13	40	0.45
Onshore wind	825[c]	0	33	n/a	25	n/a
Offshore wind	2100[c]	0	55	n/a	25	n/a
Solar PV	323[d]	0	8	n/a	25	n/a
Solar Rooftop	388[d]	0	5.8	n/a	25	n/a
Hydro reservoir[a]	2620	0	25	n/a	80	n/a
Hydro RoR[a]	3930	0	74	n/a	80	n/a
Transmission[e]	479 $/MWkm	0	9.6 $/MWkm	n/a	40	0.016 loss per 1000 km
Converter[e]	180	0	3.6	n/a	40	0.986
Battery[f]	116 $/kWh	0	0	n/a	15	0.9

OCGT, Open-cycle gas turbine; CCGT, combined-cycle gas turbine; Hydro RoR, Run-of-river hydropower.
[a]Schröder et al. (Schröder et al., 2013).
[b]IEA (Lorenczik et al., 2020).
[c]IRENA (IRENA, 2019c).
[d]IRENA (IRENA, 2019b).
[e]Hagspiel et al. (Hagspiel et al., 2014).
[f]Cole et al. (Cole and Frazier, 2019).

Cost data for the sensitivity analysis

Technology	Low Costs	Medium Costs	High Costs
Onshore wind [$/kW]	650	825	1000
Solar PV [$/kW]	165	323	481
Solar Rooftop [$/kW]	198	388	577
Storage [$/kWh]	76	116	156