Electronic Supplementary Material for:
Meeting Global Cooling Demand with Photovoltaics during the 21st Century

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1. Accounting for global warming in the temperature data

Our model inputs the temperature as a function of location and time, including the year and hour of the year. Ideally, we could directly use the results of a comprehensive climate model that evaluates such a dataset from first principles. However, due to the high time and geographic resolution required and the long timescale of the study, such a calculation would be infeasible. We thus use the following simpler model, which nonetheless captures the long-term trend of increasing global temperatures. To isolate the long-term trend, we construct a baseline year-long hourly temperature dataset $T_{\mathrm{base}}(h)$ by averaging over each hour of the year in the 21-year climate dataset[1] from year 1995 to 2005:

$$T_{\mathrm{base}}(h) = \frac{\sum_{y_d=1995}^{2005} T_d(h, y_d)}{n_{\mathrm{years}}}, \qquad \text{(S1)}$$

where h refers to the hour of the year, n_{years} is 21, or the number of years in the dataset and T_d and y_d refer to the temperature and years of the original climate dataset[1]. To then account for global warming, we use climate projections on the increase of the average global mean temperature ΔT_{mean}, and increase the base temperature of each location by the increase in the global mean temperature:

$$T_{\mathrm{input}}(h, y_{\mathrm{input}}) = T_{\mathrm{base}} + \Delta T_{\mathrm{mean}}(y_{\mathrm{input}}), \qquad \text{(S2)}$$

where T_{input} and y_{input} now refer to the temperature and year that are input to our model, and T_{mean} is calculated:

$$\Delta T_{\mathrm{mean}}(y_{\mathrm{input}}) = T_{\mathrm{mean}}(y_{\mathrm{input}}) - T_{\mathrm{mean}}(y = 1995), \quad \text{(S3)}$$

where the year 1995 is chosen because that is the average year of the 21-year climate dataset used as baseline[1]. While this approach is suitable to estimate the long-term synergy of photovoltaics and space cooling, note that this methodology does not capture the year-over-year variability in temperatures which climate change also aggravates[2].

2. Definition of world regions

Table S1 lists the countries and territories in each world region used in Fig. 4.

Table S1: Countries and territories included in each region.

Region	Countries included in the region
Centrally Planned Asia	Cambodia, China (incl. Hong Kong & Macao), Lao People's Democratic Republic, Mongolia, Vietnam
Europe & Former Soviet Union	Albania, Armenia, Austria, Azerbaijan, Belgium, Bulgaria, Bosnia and Herzegovina, Belarus, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, Ireland, Italy, Kazakhstan, Kosovo, Kyrgyzstan, Latvia, Lithuania, Luxembourg, Malta, Moldova, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Tajikistan, Turkey, Turkmenistan, The former Yugoslav Republic of Macedonia, Ukraine, United Kingdom of Great Britain and Northern Ireland, Uzbekistan
Latin America	Argentina, Bahamas, Belize, Bolivia, Brazil, Barbados, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Guatemala, Guyana, Honduras, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Paraguay, Suriname, Trinidad and Tobago, Uruguay, Venezuela
Sub-Saharan Africa	Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Congo, Côte d'Ivoire, Democratic Republic of the Congo, Djibouti, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Equatorial Guinea, Kenia, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, Swaziland, Togo, Uganda, United Republic of Tanzania, Western Sahara, Zambia, Zimbabwe
North America	Canada, Puerto Rico, United States
Oceania & Pacific Asia	Australia, Brunei Darussalam, Fiji, French Polynesia, Indonesia, Japan, Republic of Korea, Malaysia, Myanmar, New Caledonia, New Zealand, Papua New Guinea, Philippines, Singapore, Solomon Islands, Taiwan, Thailand, Timor-Leste, Vietnam, Western Samoa
Middle East & North Africa	Algeria, Bahrain, Egypt, Iran, Iraq, Jordan, Israel, Kuwait, Lebanon, Libya, Morocco, Oman, Palestine, Qatar, Saudi Arabia, South Sudan, Sudan, Syria, Tunisia, United Arab Emirates, Yemen
South Asia	Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, Sri Lanka

3. Impact of varying base-temperature during the day

The cooling demand model used in this paper makes the relatively strong assumption that the hourly cooling load closely follows changes in temperature above a base temperature of 18°C (see Eq. 2). While hotter days indeed see higher cooling demand, the specific hourly cooling load (see Eq. 7) may be affected by behavioural aspects as well: air-conditioners can for example be turned off or programmed to a higher set-point[3] when people leave their homes for work, leading to relatively smaller cooling loads in the middle of the day than estimated purely based on hourly temperature. People may also prefer lower

temperature set-points during night-time to help them fall asleep or the cooling devices may demand more electricity in the evening to maintain a fixed set point due to heat generated from preparing dinner. Because these behavioural aspects vary on local culture, customs and economic structure, it is difficult to perfectly capture these effects in a global modelling effort such as this paper.
To estimate the potential impact the omission of these aspects could have on the conclusions of this study, we use the results of Wang and Bielicki[4]. They used electricity demand and meteorological data collected from a community in the United States and fit an hourly varying base temperature for cooling demand, capturing the behavioural effects in hourly cooling dynamics. The specific base temperature used was that of the 'Temperature only' model in the PS Zone (black circles in upper left graph of Fig. 6 in Ref 4). The 'Temperature only' model was chosen as that model was otherwise closest to the model used in this paper, and the PS Zone was used due to its residential nature. The hourly base temperature is reproduced in Fig. S1. While these results are not validated globally, for this test we assume the shape of the hourly base temperature is identical in each location except for the local time zone. (For resolving the time-zone of each location, we used the python package timezonefinder[5]). To isolate the impact to only the specific intra-daily shape of the base temperature, we also scaled the base-temperature with a constant offset such that the total yearly cooling demand at each location remains identical to our model.

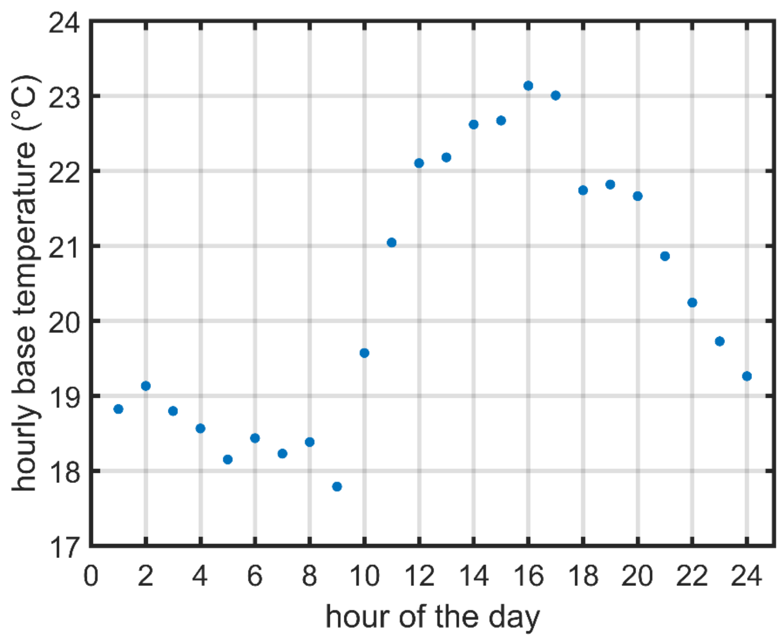

Fig. S1. Shape of the variable cooling demand base temperature investigated, taken from Ref. 4. Higher base temperature implies lower cooling demand.

Fig. S2 shows that varying the hourly base temperature does affect the amount of cooling demand that can directly be met with PV, when compared to the constant base temperature model, but does not have an impact on the conclusions of the study. More specifically, the residential cooling demand is slightly lowered during midday, describing people turning off or lowering their cooling devices setpoints when they are at work. Given that these hours exhibit high solar insolation, the synergy of cooling and PV slightly weakens and the fraction of cooling that can be directly met with PV without storage drops from 49% to 46% in 2010. The difference remains around three percentage points across the century. Similarly, with storage, the difference is approximately 2.5 %-points. However, the trends are similar regardless of the base temperature model: the synergy of cooling and PV, as well as the benefit of storage grow globally throughout the century. We also note that there is likely room for optimization in the specific synergy via orienting the PV panels to east or west and thus moving the peak PV production away from midday[6,7].

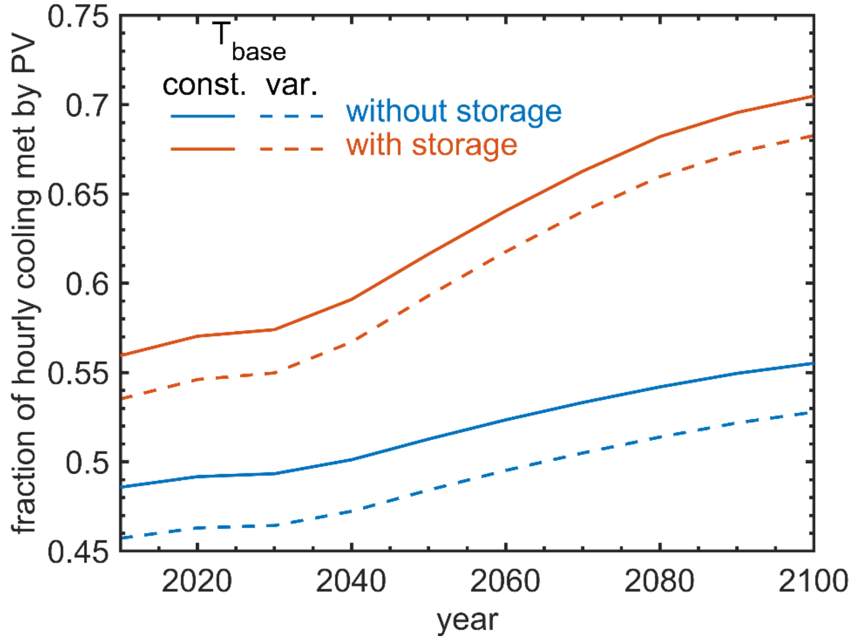

Fig. S2. Fraction of hourly cooling demand met by PV with (orange lines) or without (blue lines) storage assuming a constant (solid lines) or variable (dashed lines) base temperature.

Lastly, we note that there may be a modest lag in the cooling base temperature also between different days, because of exceptionally high thermal inertia of large buildings or because it may take a few days for people to adjust their behavior due to warming weather. While these effects could be important for short-term forecasts or when fine-tuning specific real-life systems or mathematical models, these between-days effects are smaller in magnitude[4] than the intra-day and thus their impact on the conclusions of this study is (even) smaller than the difference described in Fig. S2.

References

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