Supplementary Material

Validation of the model

To evaluate the model, we applied it to the 2016 daily mean temperature data and recalculated the demand. We then compared the modeled electricity demand with the observed one. There is a very strong correlation coefficient for the linear regressions between the electricity demand modeled and observed (r^2 = 0.95 and RMSEn = 0.055 for daily total load and r^2 = 0.96 and RMSEn = 0.053 for daily maximum hourly load, cf. Figure S1).

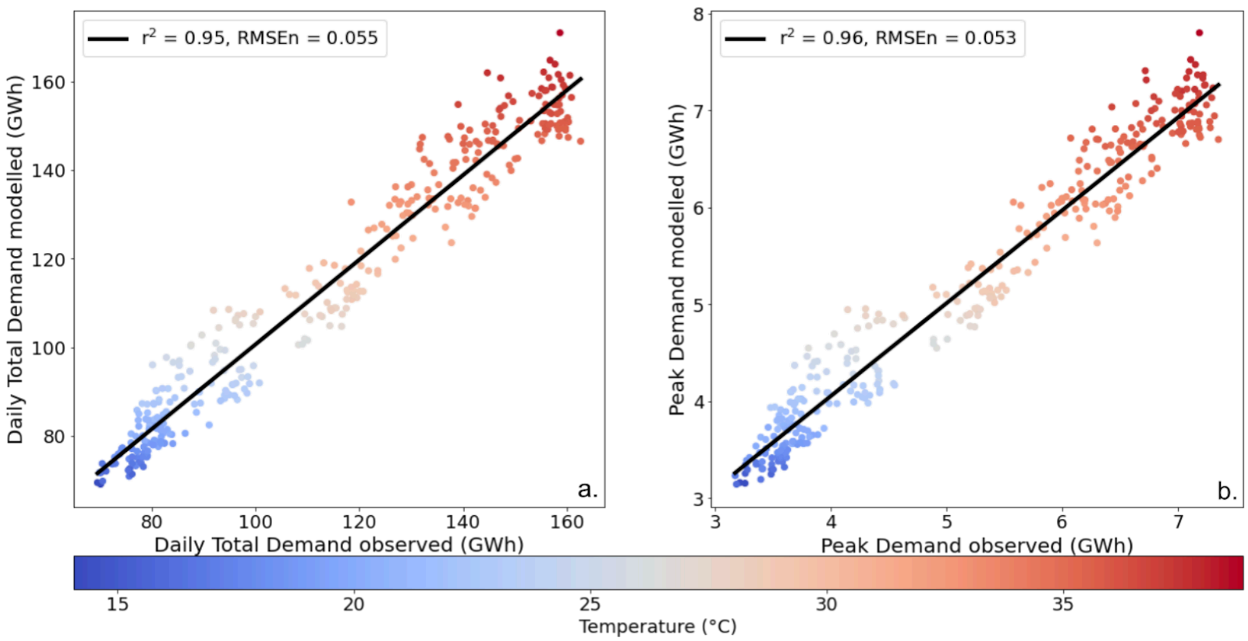

Figure S1. Actual electricity demand modeled versus electricity demand observed in Qatar for the year 2016 for daily total demand (a.) and peak demand (b.). Colors indicate the daily average temperature over Qatar.

Few official data are available to compare our results with observation but the state owned Qatari company Kahramaa, the sole producer of electricity in Qatar, published reports on its activity[28]. In particular, they released figures for the annual electricity generation in Qatar for the years 2015 to 2019, with the average for this 5 years at 45,430 GWh. The order of magnitude is consistent with our estimate. From 2014 Qatar's government also published its monthly statistics report in which they released their monthly electricity generation[29]. We did a cross validation of our results by aggregating them by month and comparing them to the government's data (cf. Figure S2). We model well the seasonal variability and our orders of magnitude are accurate. Visually it seems that our results are closer to the observations when we take into account only the effect of temperature and not the population and the GDP. The difference between our results and the observations seems to be slightly overestimated for the warmest (June, July, August) and coldest (November, December, January)months, respectively. Biases have been quantified for these two categories of months and for the simulation temperature only and the simulation temperature + population + GDP (Table S1).

	Temperature only	Temperature + population + GDP
Cold months	-0.4%	0.6%

Hot months	-1.9%	4.1%

Table S1. Biases for cold and hot months (respectively November, December, January and June, July, August) for the simulation with only the effect of temperature on the demand and the one with the effect of temperature, population and GDP expressed in percentage of difference with the government data.

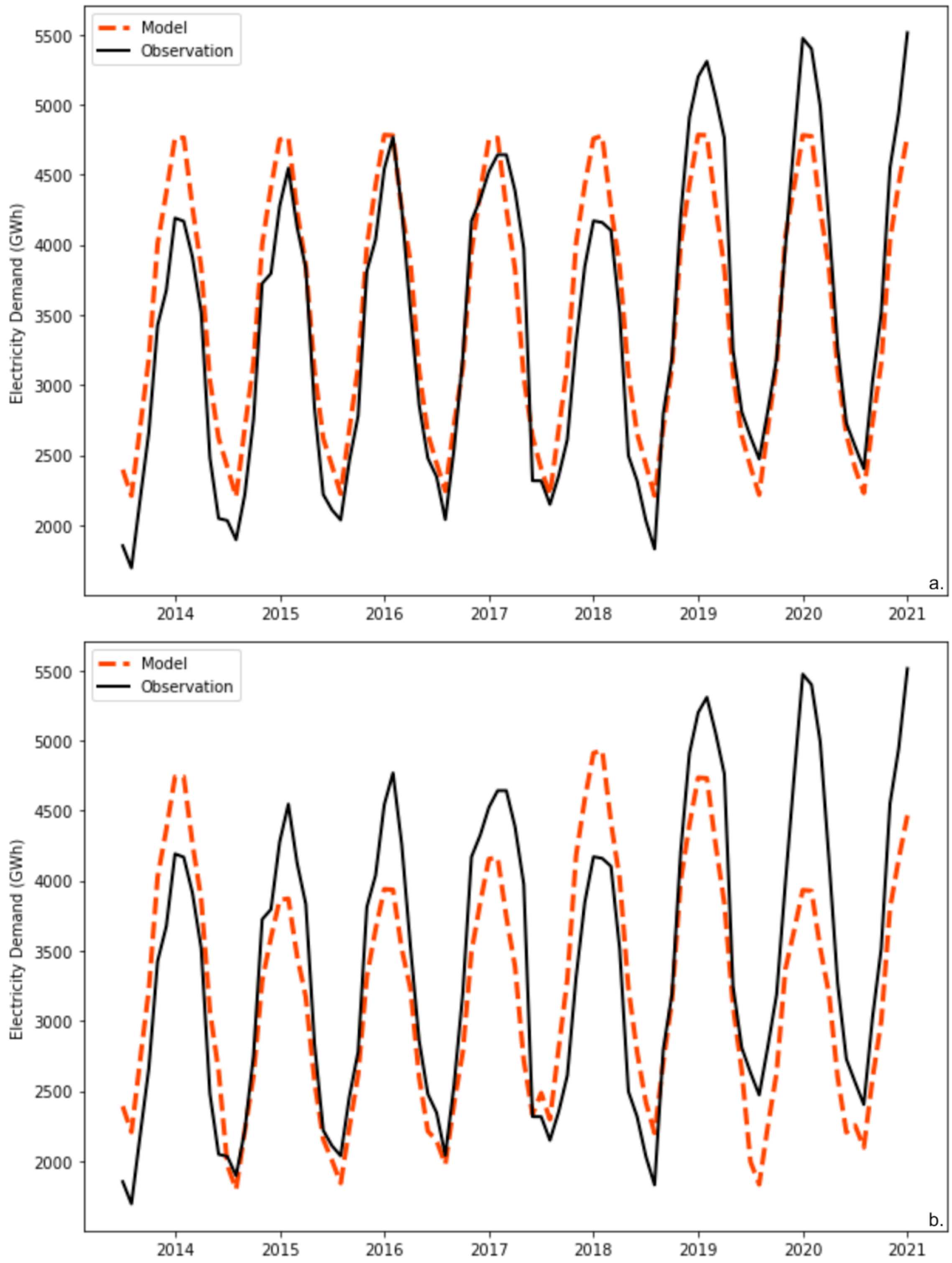

Figure S2. Comparison of monthly electricity demand reported by the Qatari government (black curves) and modeled monthly demand (dashed red curves) with the effect of (a.) temperature and (b.) temperature, GDP and population. The years indicate the month of June.

We have defined two categories of day: extremely cold days with an average temperature under 14.1°C, the 2016 minimal average daily temperature and extremely hot days above 38.8°C, the 2016 maximum daily average temperature. The values of the electricity demand calculated with our model for these days are to be taken with precaution, as they are extrapolated to a domain without data. Table S2 shows the percentage these days represents for the period 1980 - 2100. We can see that for all SSPs there are much more extremely hot days than extremely cold days and the number of extremely cold days stays constant (around 0.2%). In contrast the number of extremely hot days increases with the radiative forcing and goes from 1.2% for SSP126 to 11.5% for SSP585.

	SSP 126	SSP 245	SSP 370	SSP 585
Extremely cold days	0.27%	0.21%	0.22%	0.20%
Extremely hot days	1.2%	7.6%	9.3%	11.5%

Table S2. Percentage of extremely cold days (under 2016 minimal daily average temperature, i.e. 14.1°C) and extremely hot days (above 2016 maximum daily average temperature, i.e. 38.8°C) for the different SSPs for the whole period of study (1980 - 2100).

The model presented in this study is a statistical model based on electricity demand and temperature data. To develop this model we only had electricity consumption data for one year which was sufficient to produce a very robust relationship between electricity demand and temperature (r^2 = 0.95, RMSEn = 0.057). On the other hand, we do not have enough data of electricity demand during hot or cold waves if we want to look more closely at the response of the electricity demand to extreme temperature events, which is why in our study of extreme annual temperature and electricity demand (section 3.1.2) we took the 5% highest and lowest temperatures and not only the highest or lowest temperature of the year. Little data is available to validate the electricity demand model. By aggregating our results by year and by month, we were able to compare them to the limited data on electricity demand disclosed by the government and the company Kahramaa which allowed us to validate our model at least in terms of order of magnitude with a mean bias of ±4.1% by year (section 3.1.1). But for the study of extreme temperature and the calculation of CO_2 emissions associated with the production of electricity in Qatar it would seem that this study is the first of its kind.

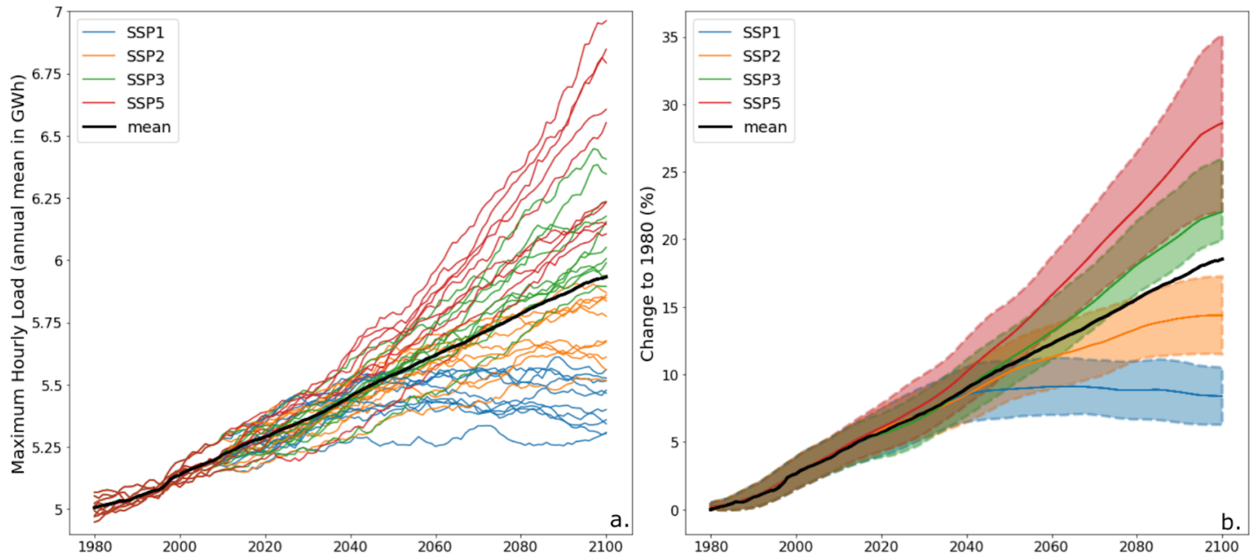

Figure S3. Daily maximum hourly demand (annual average) calculated with the quadratic model (cf. equation 3) that simulates the effect of temperature on the demand. On panel a., each curve represents the results obtained with one of the 10 models for each SSP with10-year rolling average. On panel b., it is the change in demand compared to the year 1980 (in percentage) that is represented. The thick colored lines show the average of the different SSPs and the colored areas the interval in which the 1- error is included.

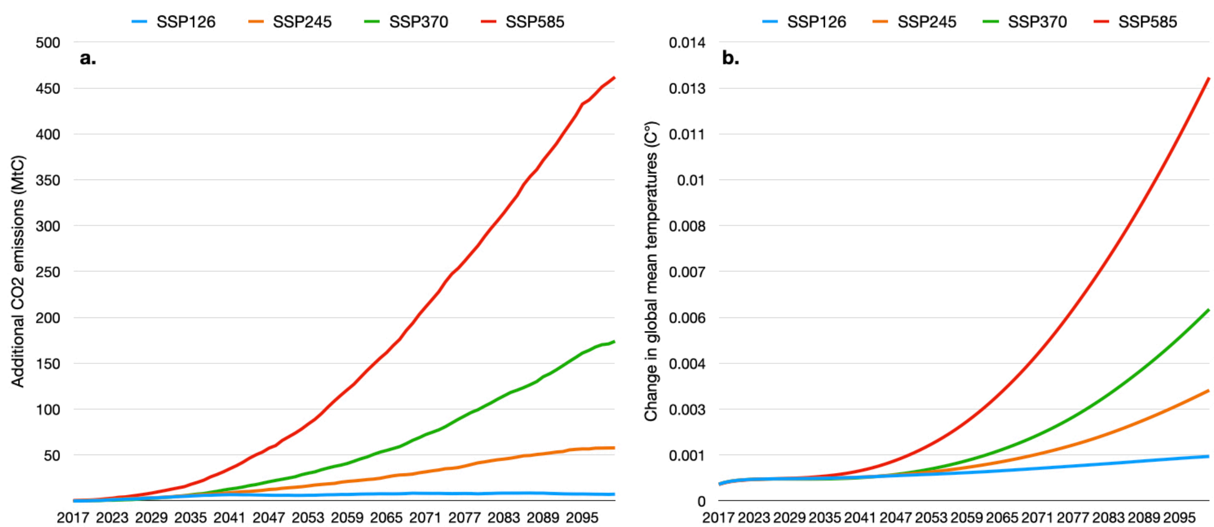

Figure S4. Additional CO_2 emissions (a.) and the resulting global temperature change (b.) obtained when we add the temperature feedback on electricity demand compared to a baseline scenario with no effect of temperature on the demand. The additional CO_2 emissions are obtained by taking the difference between the CO_2 emissions calculated with the method described in the article, i.e. by taking into account the effect of the variation over time of the 4 factors (temperature, population, GDP, and carbon intensity) and the CO_2 emissions calculated in the same way but by keeping the temperature at the 2016 level. The additional temperature change is obtained by using the simple climate model ACC2 with these additional CO_2 emissions (see main text).