Inequalities in global residential cooling energy use to 2050

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This paper

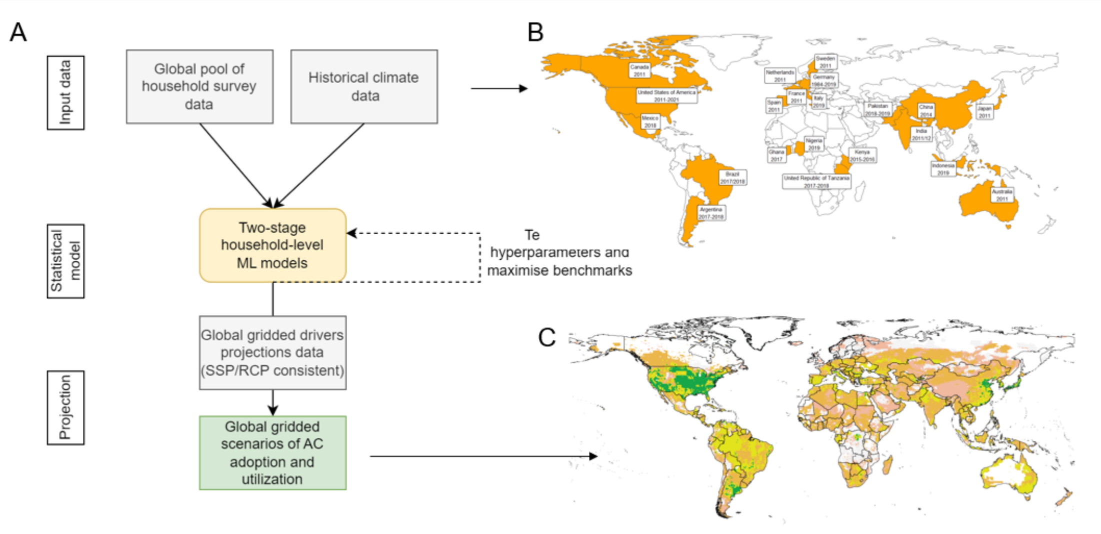
What will happen to (local) air-conditioning adoption and the consequent electricity consumption?

Objective: Produce the first global gridded data set ($0.25^\circ \times 0.25^\circ$) of **future residential air-conditioning adoption** (extensive) and **use** (intensive) for different scenarios

How:

- ↪ Collect household survey data combined with historical climate information (**ERA5**) $\Rightarrow$ training set
- ↪ **Two-stage** household level Random Forests model
- ↪ Collect gridded **projections** data of **all the included drivers** — consistent with CMIP6 RCP-SSP

What we do: simple scheme



Methods

- Top and bottom 1% observations trimmed to winsorise data
- The data set is sliced into **training set** and **test set**
- We run two Random Forests:
  1. **Classification** $\Rightarrow$ air-conditioning adoption
  2. **Regression** $\Rightarrow$ electricity quantity
- **Predicted probabilities** from classification enters into the second stage (Dubin and McFadden 1984)
- A broad array of **hyperparameters** are optimised using 10-fold cross-validation
- Model performances are evaluated using:
  1. Area under the ROC curve and Cohen's Kappa (classification) $\Rightarrow$ perform well even when events are **rare**
  2. R-squared and MSE (regression)

Results: Model Performance

Random Forest clearly **outperforms** all other ML methods

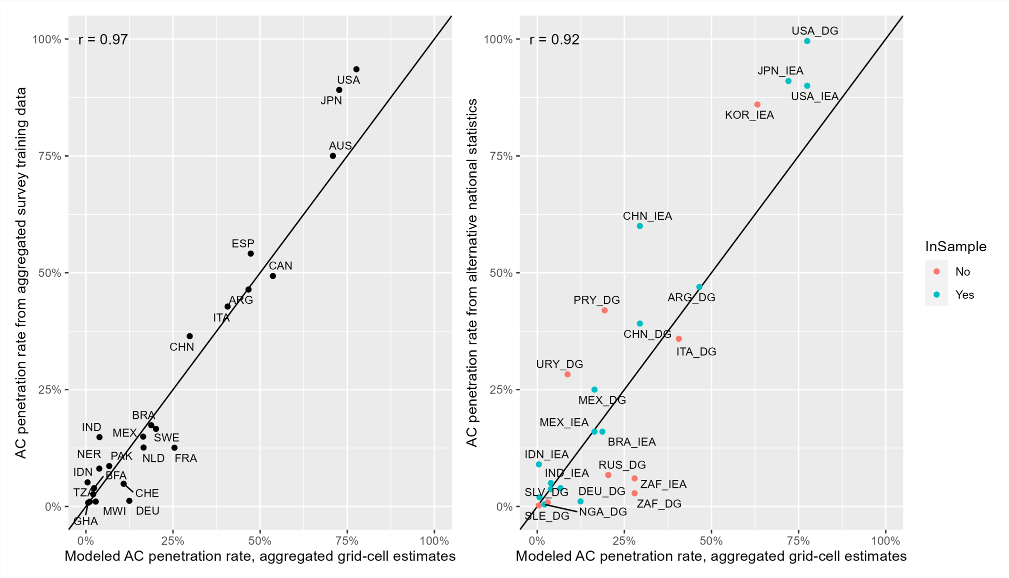
Table 1: *1st stage*

		Kappa	AUC
Model	Set	mean	mean
GLM	Training	0.64	0.80
	Testing	0.64	0.80
GAM	Training	0.63	0.80
	Testing	0.63	0.79
RF	Training	0.84	0.91
	Testing	0.73	0.87

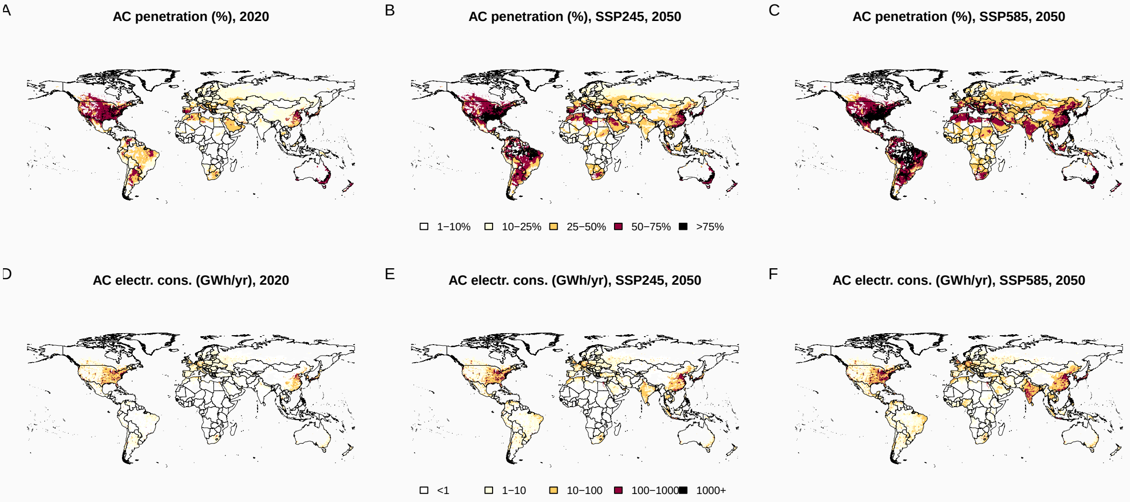
Table 2: *2nd stage*

		R-squared	MSE
Model	Set	mean	mean
LM	Training	0.51	0.69
	Testing	0.51	0.69
GAM	Training	0.59	0.58
	Testing	0.59	0.57
RF	Training	0.86	0.21
	Testing	0.75	0.35

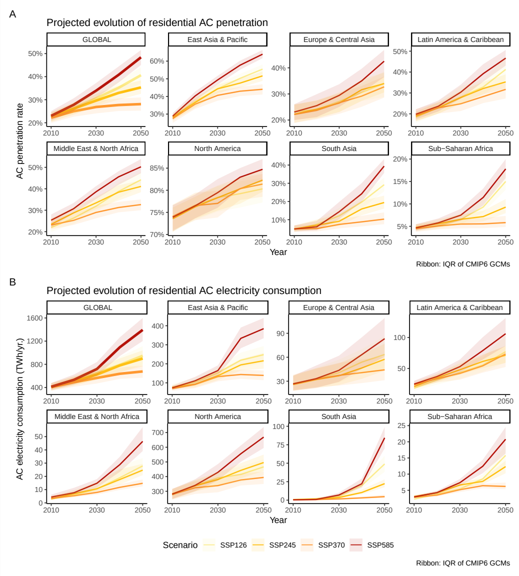
Results: External Validity



Results: Gridded Projections



Results: Trends

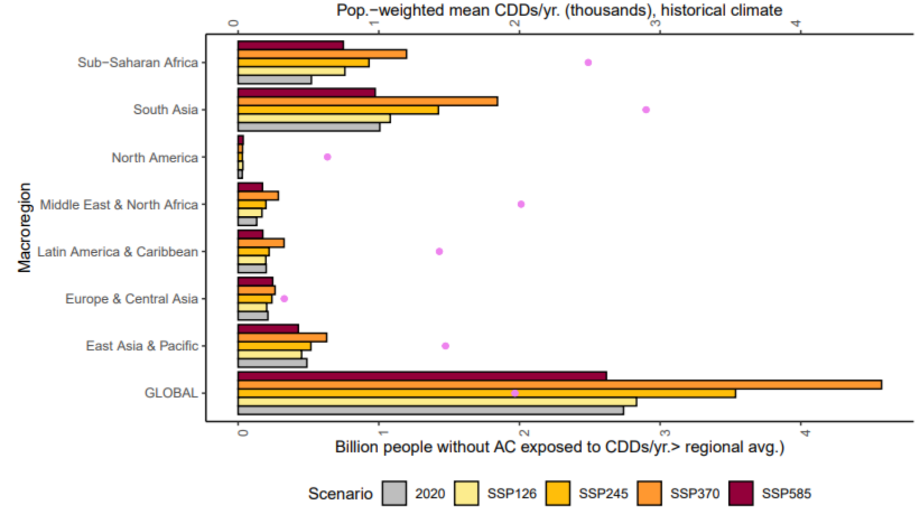


Implications: Emissions

CO_2 emissions (Mt) from electricity for air-conditioning

Region	2020	SSP126 (2050)	SSP245 (2050)	SSP370 (2050)	SSP585 (2050)
East Asia & Pacific	75.1 (62.3-90.5)	102.8 (84.9-121.5)	159.4 (128.7-189.4)	101.4 (83-120.2)	242.9 (211.1-278.4)
Europe & Central Asia	16.1 (10.7-23)	16.5 (11.7-22.4)	27.8 (20.9-37.2)	24.1 (17-33.2)	49.2 (35.8-64.5)
Latin America & Caribbean	15.7 (12.5-18.8)	14.9 (11.5-20)	29.3 (24.2-35.2)	29.1 (20.7-34.3)	54.6 (44.5-67.7)
Middle East & North Africa	3.6 (2.6-5)	8.6 (7.3-10.4)	12.6 (10.7-15.1)	9.2 (7.8-11.1)	26 (21.9-32.1)
North America	196.7 (175.7-218.7)	89.4 (78.8-99.2)	251.4 (222.2-278.8)	236.4 (209.7-260.5)	333.9 (296.9-368.1)
South Asia	1.3 (0.8-2.1)	23 (18-28.1)	16.9 (13.3-21.3)	3.5 (2.3-5.4)	58.8 (48.8-68.9)
Sub-Saharan Africa	4.1 (3.5-4.7)	5.9 (4.7-7)	9.9 (8.2-11.4)	4.7 (4.1-5.6)	15.2 (12-17.9)
Total	312.7 (268.1-362.8)	261.1 (216.9-308.7)	507.3 (428.1-588.3)	408.4 (344.6-470.3)	780.6 (671-897.7)

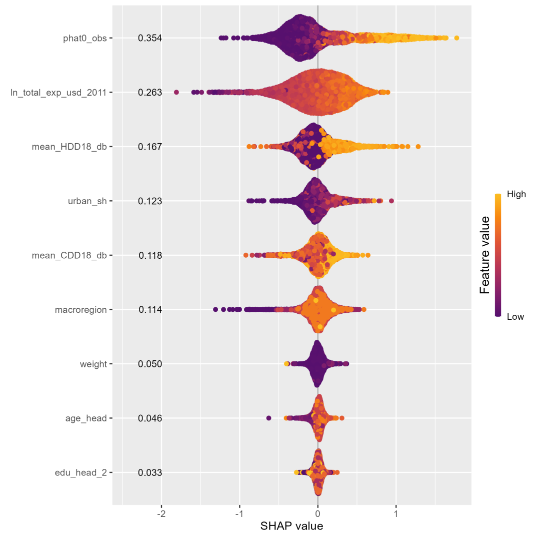
Implications: Cooling Gap



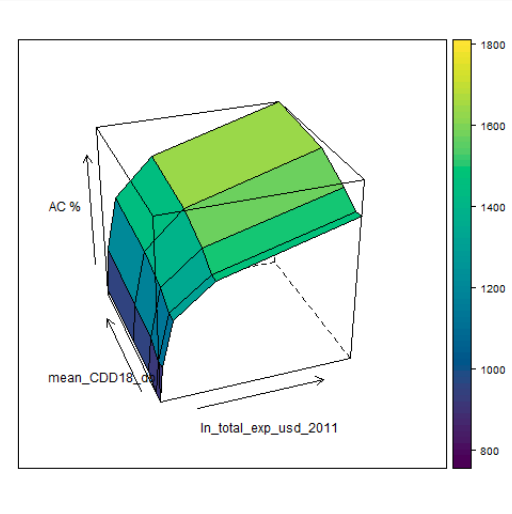
Discussion

- Huge boost in global air-conditioning penetration — **from 24% up to 50% in 2050**
- Even larger increase in electricity demand for cooling — **from 500 TWh up to 1600 TWh in 2050**
- Major implications for capacity requirements, power-sector emissions and heat adaptation inequality
- **Caveats**:
  1. No other cooling technologies considered
  2. **No causal interpretation** in the second stage $\Rightarrow$ this is a pure **prediction** exercise
  3. ML methods are somehow a black-box $\Rightarrow$ difficult to **interpret the impact of each included variable**

Discussion: Improving interpretability 1/2



Discussion: Improving interpretability 2/2



Conclusions

- We provide a new global gridded-level data set on air-conditioning adoption and use
- We use this data set to provide evidence on:
    1. inequality in the access to heat adaptation
    2. feedback on CO_2 emissions
- Random Forest **outperforms** simpler methods, but **less interpretability**
- Our data set will be available to research community to stimulate
    - Integration of air-conditioning in **IAMs, CGE models, and power system models**
    - Tests of air-conditioning as a **mediator** of heat-related impacts when no information is missing