Whose weather is it? Building a fairness framework for global AI weather models

Knowledge gap

- Al weather models display impressive performance across a range of global and regional standard metrics, potentially improving on baseline physical models (e.g. Rasp et al., 2024).
- But, are those improvements fairly distributed across different regions and demographics? For example, do high and low income regions enjoy a similar share of these improvements?

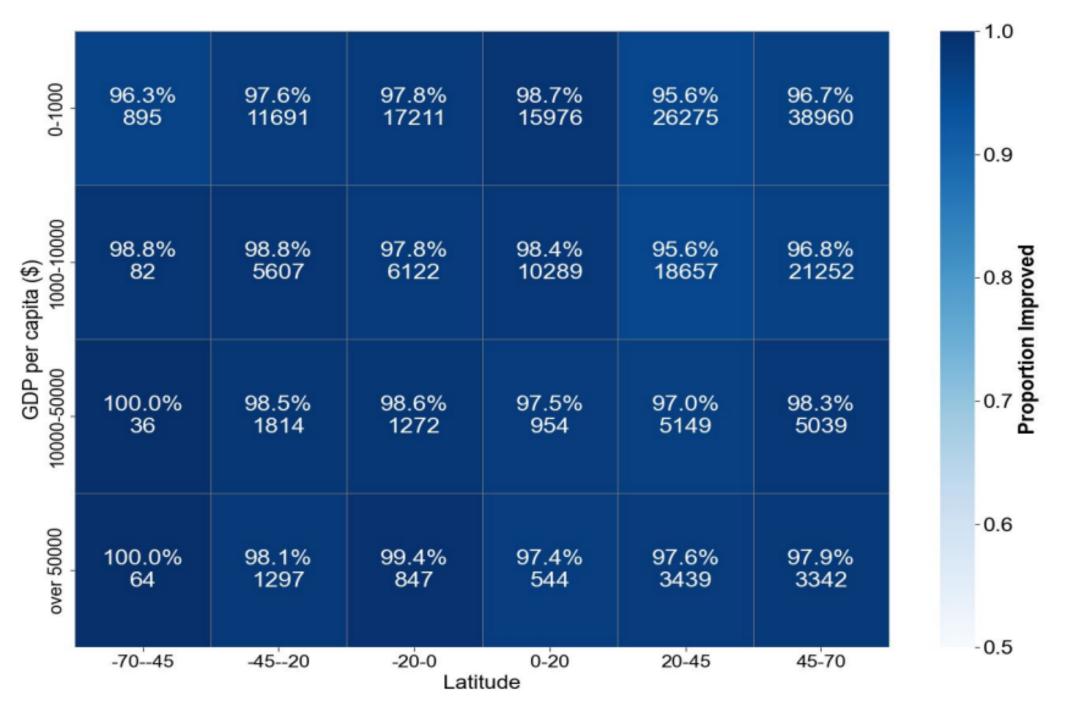
Defining fairness

- ► We focus on a narrow, outcome-based definition of fairness, following prevailing ML practices (e.g. Mitchell et al., 2021, Mehrabi et al., 2021).
- We define two key criteria, based on the proportion of grid points enjoying improvements:
 - 1. Group fairness: Improvements are equally likely across protected and non-protected groups, e.g.,
 - 2. Statistical independence: Improvements are not predicted by protected attributes, e.g.,

Criterion 1

- We compare the performance of ECMWF AIFS to IFS HRES, using ERA 5 as ground truth. Gridded population data from NASA Earth Data and GDP data from Wang and Sun, 2022.
- Does a similar proportion of low, middle and high-income grid points enjoy improved forecasts?

2m temperature



χ² (Table): p=0.000 | χ² (Rows): p=0.000 | χ² (Cols): p=0.000

Proportion of grid points with improved forecasts (lower RMSE, AIFS vs HRES), by GDP and latitude

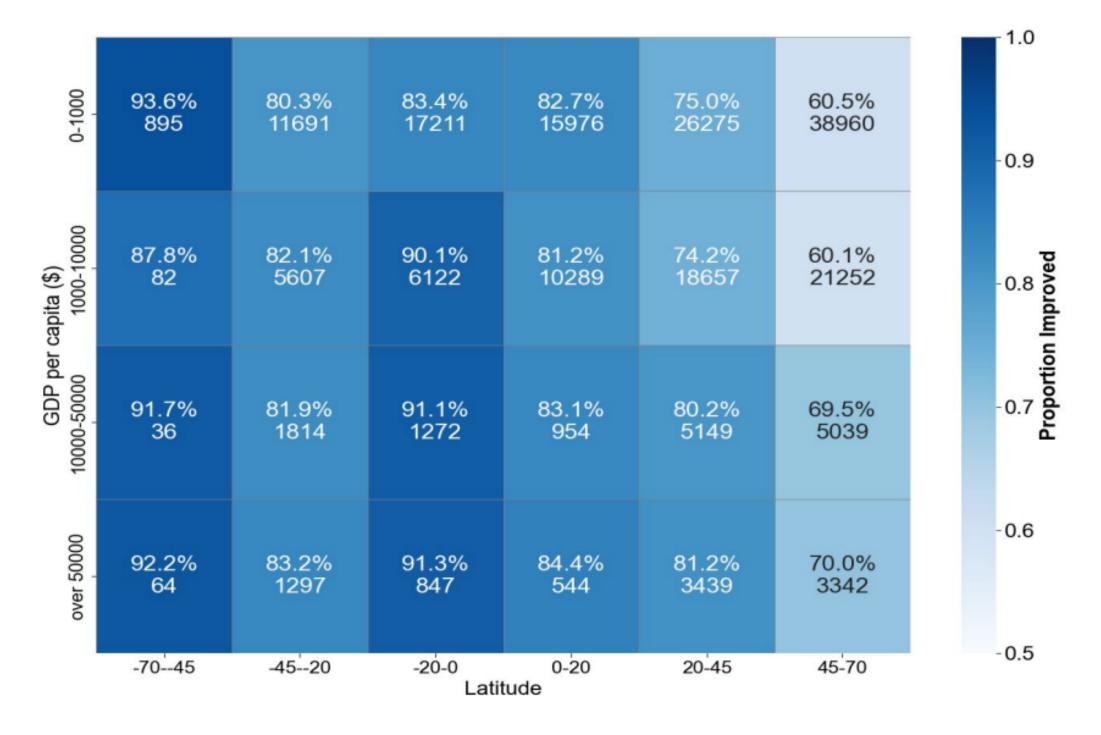
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 $p_{improved} = p_{improved_high_income} = p_{improved_low_income}$

 $\mathbb{E}(\Pr(\operatorname{improvement})) \perp \operatorname{GDP} | Z,$

where \perp denotes statistical independence, and Z is a set of control variables (e.g., latitude, longitude, elevation).

Cold extremes



 χ^2 (Table): p=0.000 | χ^2 (Rows): p=0.000 | χ^2 (Cols): p=0.000

Criterion 2

Is the probability of improved forecasts at a given grid point independent of GDP and population density?

GDP							Population density						
t2m -	1.00	0.96	1.11	0.99	1.51	-1.00	t2m -	1.18	1.09	1.08	1.09	1.15	-1.00
w10m -	1.01	1.01	1.09	1.05	1.12	-0.10 ല	w10m -	0.99	0.98	1.01	1.05	1.04	-0.10 ല
Output Variable 6 ⁻ m0tw	0.99	0.99	1.05	1.05	1.28	ected P-Value	Output Variable 6 ⁻ m01 ^m	1.08	1.01	0.98	1.02	1.00	-0.00 Corrected P-Value
t2m_05	1.01	1.00	1.00	1.01	1.11	- 0.05 0	t2m_05 -	1.17	1.14	1.12	1.12	1.28	- 0.05
t2m_95 -	0.99	0.99	0.99	0.99	0.98		t2m_95	0.98	0.98	1.03	1.09	1.02	0.00
l	ັ່ງ ທີ່ 1 ເບັດ Lead Time (Days)							່າ ຈໍ່ຈໍ່າ Lead Time (Days)					-0.00

Standardised effect of GDP and population density on odds of improved forecast for a given output variable, lead time and grid point, estimated through logistic regression. Output varibles: 2m temperature, 10m windspeed, windspeed extremes, cold extremes, hot extremes.

Main conclusions

AIFS superior to IFS HRES across most regions and demographics - "better forecasts for everyone", but to different extents.

Neither fairness criterion is fully satisfied. On average, AIFS works best in densely populated areas with high income.

Much left to be investigated - both for AIFS and other AI models!

Possible solutions?

Embed fairness criteria in the loss function (fairness through awareness):

Weighting schemes to compensate currently disadvantaged grid points. Penalty terms discouraging uneven performance.

Resources and skill transfers are also a possibility.

Defining fairness criteria and monitoring their fulfilment are key initial steps.



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