Climate information granularity and projections of physical risk impacts on economic outputs: A spatial *momentum* has started

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Outline of Session

- 1) Climate change impacts space and sectors heterogeneously: why are global averages less reliable?
- 2) What are the latest climate simulation developments driven by NASA and other mega-providers and what should it tell us about the transformation of our sector?
- 3) What does "higher granularity" mean, and why is it crucial for physical risk assessments and our ability to adapt to future shocks?
- 4) Using the Mediterranean basin as a case study, how can we project climate shift impacts on economic outputs and how to distribute resulting estimates over time and space?
- 5) Dealing with uncertainty: a measure of how much we have yet to understand, so how to account for it?
- 6) Moving forward: what are the implications for investors in search of regional guidelines?



Climate change impacts space heterogeneously Geography is a fixed statistic, unlike climate.



Fig. 1: Surface air temperature anomalies in 2024 Source: ERA5 – reference period is 1991-2020. Credit: C3S/ECMWF





Fig. 2: Crop **supply** [*left*] vs. energy **demand** [*right*] responses to temperature.

Source: Schlenker and Roberts (PNAS, 2009), https://www.pnas.org/doi/10.1073/pnas.0906865106 Auffhammer et al (PNAS, 2017), https://www.pnas.org/doi/10.1073/pnas.1613193114

Why are global averages less reliable?

2024 confirmed as the hottest year on record

Global average temperature relative to a preindustrial baseline, C



Guardian graphic. Source: Copernicus, ERA5. Notes: Relative to a 1850-1900 baseline

Climate: intra-region heterogeneity stories?



Why are global averages less reliable?



Fig. 3: Global average projected GDP per capita loss in 2100 (SSP5) for different levels of global mean temperature increase, relative to pre-industrial temperatures. Source: Burke et al (Nature, 2015): https://www.nature.com/articles/nature15725

Economics: sectors, industries, and asset class-specific risk exposure?

Yet, decision-makers and particularly investors are increasingly in search of regional guidelines...

U.S. Securities and Exchange Commission (SEC) and the 'Climate Disclosure Rules'

March 6, 2024, the U.S. SEC adopted new climate-related disclosure requirements (the "Climate Disclosure Rules"):

These rules mandate that public companies include in their audited financial statements to investors, both quantitative and qualitative information on their 'Activities to <u>Mitigate</u> and <u>Adapt</u> to Climate Risks'.





What is missing here?

What are the latest climate simulation developments driven by NASA and other mega-providers (I)?



SERVICES HOME SUPERCOMPUTING CLOUD VISUALIZATION DATA SHARING & TOOLS CDS

// NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6)

'Big' climate datasets are now freely accessible on cloud repositories (an 'Alexandria Library').

Datasets are ensembles of highly-time and -spatially resolved gridded climate information, whether of historical measurements or simulated forecasts matching climate change scenarios (i.e., RCPs/SSPs).

These products are heavy (~few Tbs to 150 Tbs) and with idiosyncratic file structures (multi-band netcdf raster layers, etc.); and require High performance Computing (HPC) systems.

What are the latest climate simulation developments driven by NASA and other mega-providers (II)?

See below: [top-left] Terra package for large geospatial products (Rstudio); [top-right] Highmemory node on SCC Cluster (Linux); [bottom-left] Google Earth Engine (JavaScript); [bottomright] Microsoft Planetary Computer (Python) etc... Hands-on!

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What does "higher granularity" mean, and why is it crucial for physical risk assessments (I)?

For long, approaches to climate change were very much '*temporal*'.

Communication conventions generally narrow down risks to one global figure target over a long-term window (e.g., , 2015 Paris Agreement target of limiting the global surface average temperature below 1.5 deg. C by 2050).

Similarly for macroeconomic insights. E.g.; 'Climate change costs the world 12% in GDP losses for every 1°C of warming', World Economic Forum, June 6th 2024, about: Bilal, A., & Känzig, D. R. (2024). The Macroeconomic Impact of Climate Change: Global vs. Local Temperature (No. w32450). National Bureau of Economic Research (NBER).



What does "higher granularity" mean, and why is it crucial for physical risk assessments (II)?

Yet, we know that:

- The frequency and intensity of climate shocks will keep increasing.
- Their distribution across locations will be increasingly heterogeneous. e.g., January 2025: Wildfires in Los Angeles, California; snowstorms in Texas.
- ✓ **There is a burgeoning availability** of highly-resolved climate information.

So, should we use these data to project & locationally distribute future physical risk impacts on outputs? **Yes**, <u>because we can</u>.

'Granularity' = Approaching climate shocks spatially; giving increasing attention to shorter-time windows; and measures of extreme events.



How can we project climate risk impacts on economic outputs and how to distribute resulting estimates over <u>time</u> and <u>space</u>?

Let's use the Mediterranean basin as a case study.

Say some industry is interested in climate-related regional damages to the most aggregated output (GDP) and has asked us to <u>elaborate and</u> <u>deliver a product</u> focused on this region. How can we project climate risk impacts on economic outputs and how to distribute resulting estimates over <u>time</u> and <u>space</u>?

We could propose the following stepwise strategy:

Step 1: Large-scale processing of historical economic and climate information.

Step 2: Econometric estimation of temperature-output response functions using the datasets assembled in *Step 1*.

<u>Step 3:</u> Projections of future climatically-driven changes in outcomes, calibrated via our econometrically-structured equations in *Step 2*.

<u>Step 4</u>: Decomposition and distribution of resulting projected impacts obtained in *Step 3* over multiple vectors: time, space, climate scenario, global climate model, etc.



Step 1: Large-scale processing of economic information (I)







Source: EDHEC Climate Institute using https://gadm.org/data.html

Step 1: Large-scale processing of historical climate information (II)

Using HPC, we handle large-scale processing of high-resolution time- and spatially downscaled historical 3h 0.25-degree gridded surface climatic exposure (and air column-averaged satellite/remote sensing measurements) from NASA's Global Land Data Assimilation System (GLDAS) reanalysis data; e.g., Temperature and precipitation;



Fig. 5a. Map of the 2000-2015 linear trend in average temperature in each of the 249,000 unique 0.25 \times 0.25 grid-cells from NASA's Global Land Data Assimilation System (GLDAS) and covering all land surfaces globally. A *T* trend of 1.0 means that temperatures at the end of the period were 1.0 σ higher than at the beginning of the period -- **this is climate shift** (Source: EDHEC Climate Institute).



Step 1: Matching (III)



Fig. 5b. We spatially intersect GLDAS grid-cell coordinates with the different sub-national administrative region identifiers in which they fall.

Which we spatially aggregate (1) prior to temporally collapse (2) to the spatial resolution and time-frequency of our sub-national GDP realizations;

We use various weighting methods to account for heterogeneously distributed population density intra-provinces etc.

Administrative areas' real gross regional product per capita data are taken from the MCC-PIK Database of Subnational Economic Output (DOSE) containing 1,661 sub-national regions; from which we subset the Mediterranean Basin. Using exchange rates from the FRED, we convert values from local currencies to US dollars to account for diverging national inflationary tendencies and then account for US inflation using a deflator



Step 1: What if we had to dive deeper?

- A least bad solution is to process spatially-downscaled economic products;
- Globally gridded yearly real GDP product that spatially aligns satellite-derived calibrated nighttime light data from radiometer measurements with WDI/PWT national time series of economic production achieved by year;
- Ultimately downscaled on a 1 km x 1 km grid; available in Scientific Data.





Source: Gianluca D. Muscelli

Source: Erlat and Güler (2024)

Step 2: Econometric estimation of temperature-output response functions

We now have an estimation dataset linking:

Year-to-year historical records of gross regional product per capita with plausibly exogenous variations in climate over matching time periods;

We exploit two sources of climate-induced random variation (interannual and cross-section) in a panel Fixed Effects (Fes) Ordinary Least Square (OLS) framework;
 In our *econometric artillery*, we control for unobserved spatially- and temporally varying trending factors correlated with climate and likely to affect output.

Fig. 6. Global non-linear log[Gross Regional Product per capita] responses to administrative province annual average temperature exposure per year [deg. C]; EDHEC (red) vs. Burke et al 2015 (blue). (Source: our elaboration at EDHEC Climate Institute).

<u>Step 2:</u> Robustness Check—Is Fig. 6 generalizable or a composite effect?

Global non-linearity is driven by differences in countries' average temperature, not GDP.
 Orange dots and lines show the point estimate and 95% CI for the marginal effects of temperature on GDP per capita growth evaluated at different temperature baselines estimated from a model interacting each country's year-to-year temperature fluctuation with its own average over the sample period.

 Orange dots and lines show equivalent point estimates between models that include/exclude an interaction between annual temperature and average GDP per capita.
 The non-linear response in Fig. 6 is not due to hot countries being poorer on average.



Fig. 7. Global log[Gross Regional Product per capita] marginal responses to different administrative province annual average temperature <u>baselines</u> [deg. C] (Source: our elaboration at EDHEC Climate Institute).

Step 3: Projections of future climatically-driven changes in outcomes (I)

....

We can compute projections of future climate shift-driven changes in output, by 'forcing' an ensemble of climate change simulations into our regional GDP model; which we have econometrically calibrated in Step 2 using real historical data.

Step 3: Projections of future climatically-driven changes in outcomes (II)

To do so: process and extract high-resolution simulations of climate change driven shifts in temperature and precipitation exposure from NASA's Earth Exchange Global Daily Downscaled Projections (NEX-GDDP CMIP6); which we subset over our area of interest.

NEX-GDDP CMIP6: ensemble of 30 distinct global climate models (GCMs) simulated under the Coupled Model Intercomparison, Phase VI (CMIP6) exercise, whose outputs are biased-corrected and downscaled in time (to days) and space (to a 0.25 deg. grid).

NEX-GDDP CMIP6 is a large-dimensional matrix (Tb-sized) and must be combined with HPC; 249,000 unique grid-cell-level information x 365 days x 30 GCMs x 2 RCPs gives you 5.4 billion rows ... by year of data.



Step 3: Projections of future climatically-driven changes in outcomes (III)



Left: Picture of computer cabinets located in the German Climate Computing Centre which form the supercomputer "Mistral" (Source: Felix König).

Fig. 8. Snapshot of NASA 0.25 deg. downscaled projections (NASA NEX-GDDP-CMIP6) of monthly median surface temperature in degree Kelvin for 2050 (Source: ASDI).



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Step 4: Decomposition and distribution of resulting projected impacts (I)

 \triangleright Resulting projected fractional changes (% or absolute Δ) are decomposed; For each sub-national administrative province of the Mediterranean basin, we have estimated a unique vector containing > 2,000 unique simulated GDP impacts distributed across:

- Climate components (e.g., temperature, precipitation etc.); 1)
- 2) Intensity of effects (e.g., long stochastic average vs. extreme weather event);
- 3) Intensity of persistence (e.g., short-run, lagged long-run);
- 30 Global Climate Models (GCMs); 4)
- 5) 4 RCP/SSP scenarios (e.g., SSP2.RCP4.5, SSP5.RCP8.5 ect.);
- 6) Epochs: 2030, 3035, ..., 2100; totaling ~25 M. dim.



Fig. 9: Spatially distributed province-level projections of climatically-driven average *temperature* shift impacts (%) on gross regional output per capita, epoch 2099 compared to historical baseline. Color gradient shows the multi-model median impacts of 15 'likely' CMIP6 global climate models (GCMs) simulated under a SSP5-8.5 vigorous warming scenario (Source: EDHEC Climate Institute).



<u>Step 4:</u> Decomposition and distribution of resulting projected impacts (II)

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Climate Impac

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Dealing with uncertainty: a measure of how much we have yet to understand, so how to account for it?

Estimates of the macroeconomic effects of climate change are GCM-sensitive (Burke et al, 2015).

Another concern is that a subset of CMIP6 GCMs may be "too hot": higher-thanconsensus global surface temperature response to doubled atmospheric CO2 concentrations (ECS) and to a 1% per annum increase in CO2 over 70 years (TCR).

Climate sensitivity in CMIP6 models



We follow Hausfather et al's (2022) recommended procedure of excluding models with TCR and ECS outside "likely" ranges (1.4-2.2°C, 66% likelihood, and 2.5-4°C, 90% likelihood, respectively).



Conclusion (I)

Recall the case: Say that some industry is interested in climate-related regional damages to the most aggregated output (GDP) and has asked us to elaborate and deliver a product focused on this region.

This application can elaborate a panel dataset of annual province-level gross regional product per capita and empirically quantify the regional temperature and precipitation responses for sub-national regions responsible for 95% of global economic production in the Mediterranean basin.

We can then project climate change-driven temperature shift impacts on gross regional product, by 'forcing' an ensemble of CMIP6 global climate models (GCMs) gridded simulations over a wide range of future epochs (2030, 2035, ..., 2100) into our regional GDP model; which we have econometrically calibrated using real historical data.





Conclusion (II)

We can use a multi-model median subset of 15 'likely' GCMs to form the basis of our economic impact projections.

Resulting simulated output impacts can then be distributed over time, space and warming scenarios to more granularly identify future physical risk hotspots <u>and</u> <u>draw heterogeneity stories intra-country.</u>

If country-averaged, estimated shocks to outputs can be forced into a <u>Computable General Equilibrium (CGE) model</u> or IAM to quantify other macro implications (trade balances, pricing, sectors) after adjusting for external parameters.



Moving forward: what are the implications for investors in search of regional guidelines (I)?

Estimates of global economic damages have granular origins that we explore and exploit to inform investors and large physical asset-owners.

Natixis' Flash Economics communication of June 27th, 2024; P. Arthus: 'if recent estimates of the effect of global warming on global GDP are correct, *investment to avoid global warming is the most profitable of all investments*.'

There is a near-certain likelihood of incoming extreme events, more intense and frequent over time.

At EDHEC, we advocate that:

→ Funding for global warming MITIGATION requires parallel investments to strengthen cities' and industries' ADAPTATION capacity.



Moving forward: what are the implications for investors in search of regional principles (II)?

Our work aims to support this shift towards accounting for adaptation in investment management by answering three key questions that are particularly relevant for investors seeking regional climate risk solutions:

1. What is the size of future climate shocks at the local level, and how do they distribute spatially and scale up globally?

- 2. How much will it cost (% vs. absolute terms)?
- 3. Who will have to pay? (+Asset pricing implications?)



Moving forward: what are the implications for investors in search of regional guidelines (III)?

Climate change is a global public good problem that leaves no productive unit or location untreated. In 2023, 62% of global disaster losses were uninsured (Financial Stability Board, 2025).

E.g., real-estate industry in the U.S., currently 2.6 million homes (valued at \$1.3 Trillion) rated at moderate or severe wildfire risk alone.



Fig. 11. Insurers are deserting homeowners as climate shocks worsen. (Source: U.S. Senate Budget Committee, 2024).

Conclusions

Note that this case study is only a brief example of what a real-world *feasible* application to a macro/aggregated output could look like.

More/less complex sequential workflow, focusing on sectors or direct assets for instance, can also be deployed.

If you want to find out more on the topic, please see:

N. Schneider, (2024). Refining Risk Assessments with High-Resolution Climate Simulations and Advanced Econometric Modeling, EDHEC Climate Institute, December 2024, <u>https://climateimpact.edhec.edu/refining-risk-assessments-high-resolution-climate</u>

N. Schneider, (2025), From Global Averages to Local Insights: Harnessing High-Resolution Data for Climate Risk Assessment and Resilience to Physical Shocks, Investments & Pensions Europe. Forthcoming.

R. Rebonato, D. Kainth and L. Melin, (2024), *The Impact of Physical Climate Risk on Global Equity Valuations*, SSRN working paper, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4804189









Thank you!

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