Interactive Visualization of Climate Data

NCAR | NATIONAL CENTER FOR ATMOSPHERIC RESEARCH

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Background and Objectives

- Interactive visualization can **accelerate scientific discovery** and help **communicate results clearly** and **intuitively**.
- **Climate datasets** can be **complex** and difficult to understand - *spatial and temporal trends, regional vs. local effects, ensemble predictions, etc.*

Which tools to use and how to effectively visualize climate datasets?

Objectives

- *Build a dashboard* for the CESM LENS2 climate dataset.
- *Explore* and *compare* different dashboarding solutions.

Data

CESM LENS2

CESM2 Large Ensemble Community Project

1°×1° Spatial Resolution	1° ≈ 49 miles near Denver
Historical & Future climate	1850-2100
Ensemble Simulation	100 members
Two forcing types	CMIP6 and SMBB
Total raw data size	70 TB

For more information please visit
https://www.cesm.ucar.edu/community-projects/lens2/data-sets

Pre-processing

- **Annual Mean** and **Standard Deviation** across ensemble members.
- 8 variables ~400 MB each
- Obtained the raw CESM LENS2 dataset from AWS using Intake-ESM.
- Used Dask for pre-processing on Casper using the PBS Scheduler

Methods and Resulting Dashboards

We considered two approaches for building the dashboard - (i) using the HoloViz ecosystem, which provides *high level python packages for interactive plotting*, and (ii) a custom client-server model, where an *API server at the backend serves data* and the frontend plots the data and handles interactivity.

1. HoloViz Ecosystem

Variable plotted on a map for selected year and forcing type.

Bokeh interaction toolbar options:

- **Box select**: select a region to plot regional average in the time-series plot.
- **Tap tool**: if toggled on, clicking on map will load time-series of that location.
- **Scroll-wheel zoom**: toggle if the mouse scroll-wheel zooms in & out.
- **Save**: save the image as a png file.

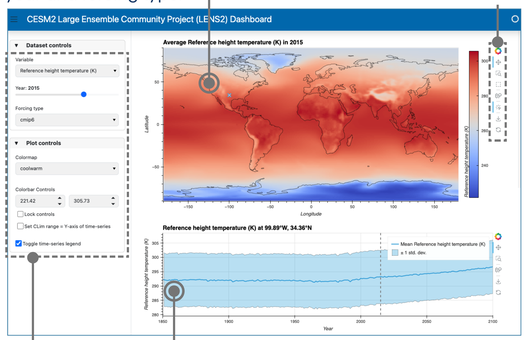


Figure: Resulting dashboard

Controls allow changing variable, year, forcing type and colormap related configurations.

Time-series of the variable for a location. Clicking on any point on the map will update this time-series plot. The shaded region displays the ±1 standard deviation, representing the model uncertainty.

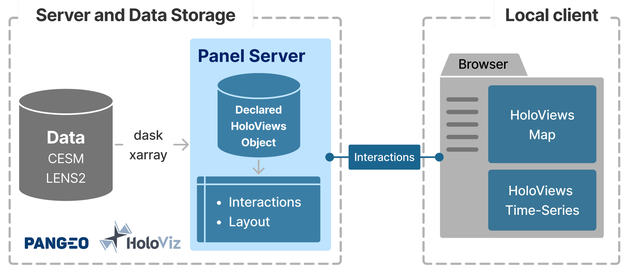


Figure: Conceptual diagram of the HoloViz dashboard

+ Dashboard can be built either in Jupyter notebooks or as python scripts.
+ Allows building dashboards solely using python.
− Complex customization can be difficult to implement

2. Custom Client-Server

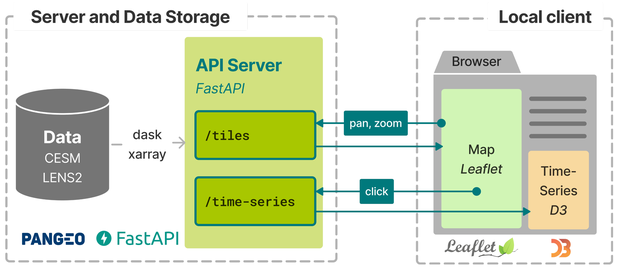


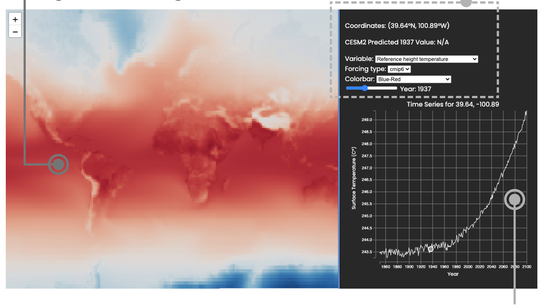
Figure: Conceptual diagram of the custom client-server dashboard

+ Minimal overhead - higher ceiling for performance.
+ D3 provides more customization and interactivity options.
− Server-client communication has to be explicitly designed unlike the HoloViz ecosystem where it is abstracted away from the developer.

Variable plotted on a map for selected year and forcing type.

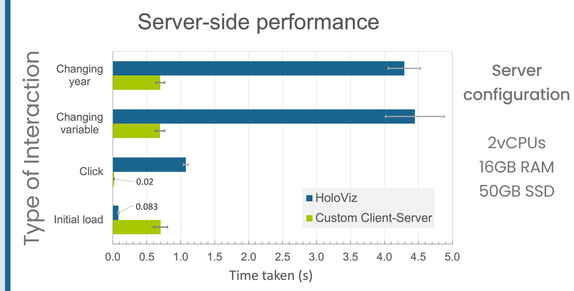
Plotting controls: Allows users to change variable, forcing type, colormap and the year which is being plotted on the map.

Figure: Resulting dashboard



Clicking on the map plots the time-series of the selected variable for that location.

Performance Results



- Overall performance was better in the custom client-server model based dashboard.
- Although the custom solution was faster, it demanded significantly more coding and personnel time, while the HoloViz ecosystem proved relatively easier to develop the dashboard using tools familiar to scientists..

Conclusions and Future work

HoloViz

- Quicker to get started.
- Integrates with existing tools - jupyter, xarray, dask, *etc.*

Custom Client-Server

- Higher performance can be achieved.
- Development time is high and can requires more design considerations.

Best suited for **Exploration** and **Analysis**

Best suited for **Results** and **Science Communication**

negin513/
LENS2-Dashboard-Python

NCAR/
LENS2-Dashboard-D3

Future work to look into - (i) caching for better performance, (ii) optimizations to callback functions and API calls and (iii) containerized deployment to cloud services.

References and Acknowledgments

Rodgers, K. B., Lee, S.-S., Rosenbloom, N., *et al.*: **Ubiquity of human-induced changes in climate variability**, *Earth Syst. Dynam., 12, 1393–1411*, doi: 10.5194/esd-12-1393-2021, 2021.

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