



ENABLING TRANSFORMATIONAL SCIENCE

PANGEO DEPLOYMENT AT NCI

5th Feb 2021



Special thanks to all supporters:



Agenda

Time	topic
11:00-11:20	Overview of Pangeo Deployment at NCI (<i>this presentation</i>)
11:20-11:40	Documentation and Live demo of setting up Pangeo (<i>this presentation</i>)
11:40-12:00	Q&A and 10min break
12:00-12:10	Introduction to VDI and NCI-data-analysis environment
12:00-12:30	Overview of Xarray and Dask
12:30-12:45	Live demo
12:45-1:00	Q&A and wrap up the workshop

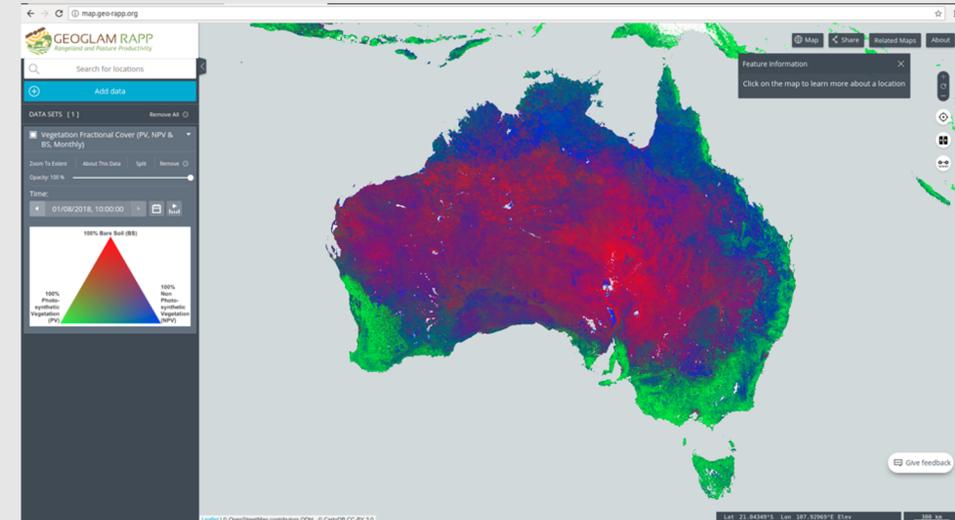
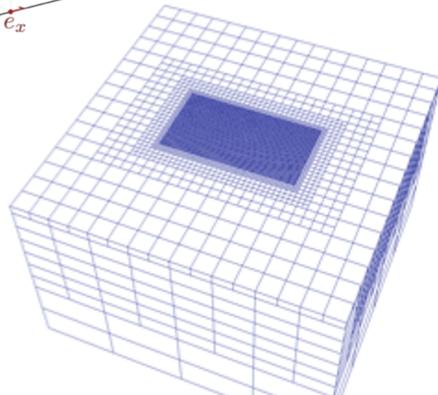
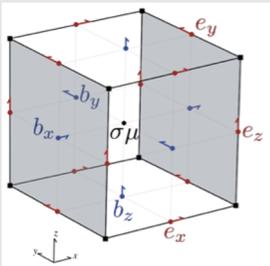
WHAT DRIVES PROGRESS IN (GEO)SCIENCE?

$$\nabla \times \mathbf{e} = -\frac{\partial \mathbf{b}}{\partial t}$$
$$\nabla \times \mathbf{h} = \mathbf{j} + \frac{\partial \mathbf{d}}{\partial t}$$

Theory &
Ideas

Observations
/ Data

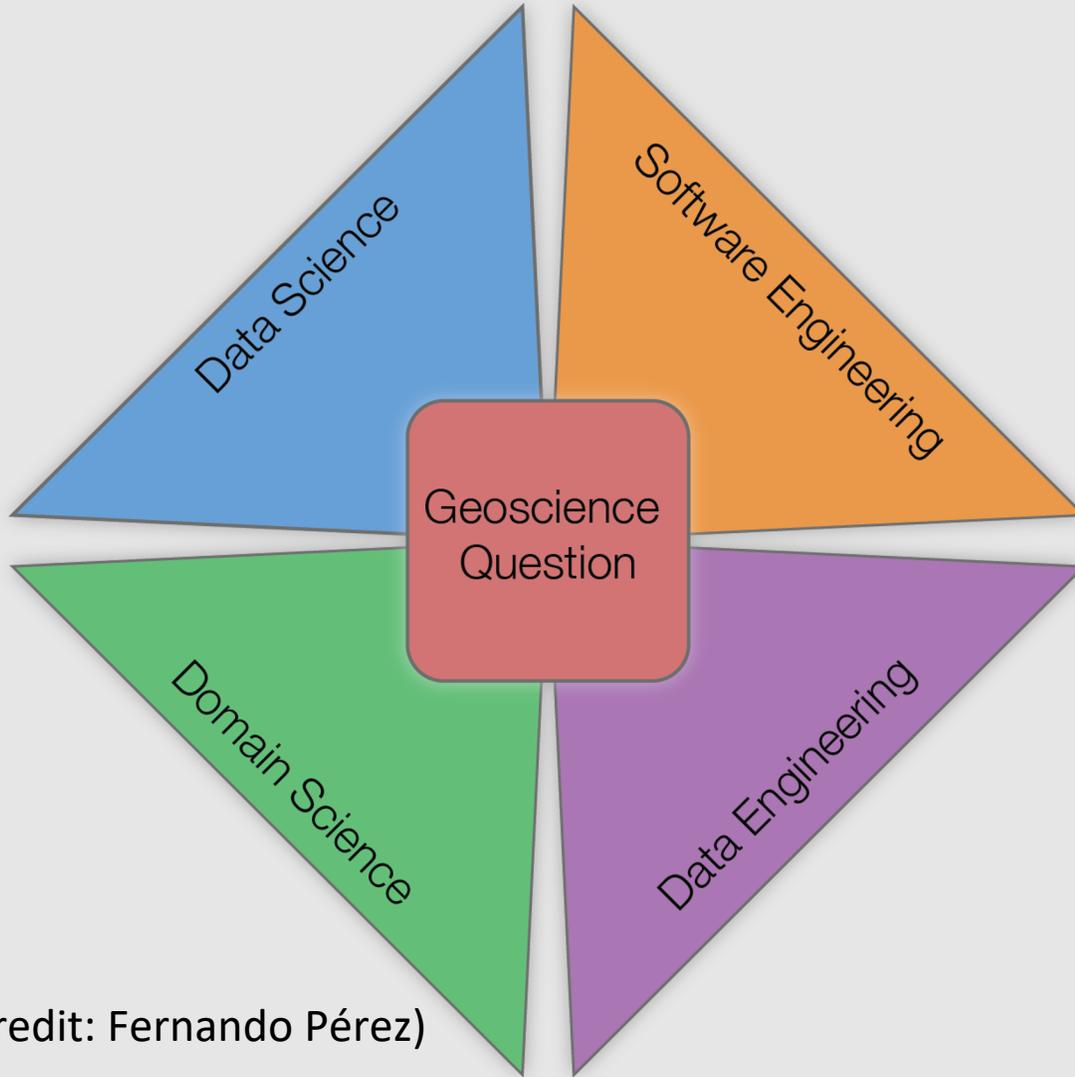
Simulations,
Computatio
n



(MODIS Fractional Cover loaded on the GEOGLAM RAPP map)

(Credit: Fernando Pérez)

ULTIMATE GOAL: REALLOCATE TIME!



(credit: Fernando Pérez)

Traditional Way



With data, software and compute available...



PANGEO

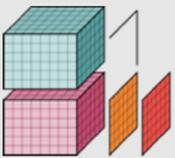
Harnessing the power of cloud computing to study the whole Earth interactively



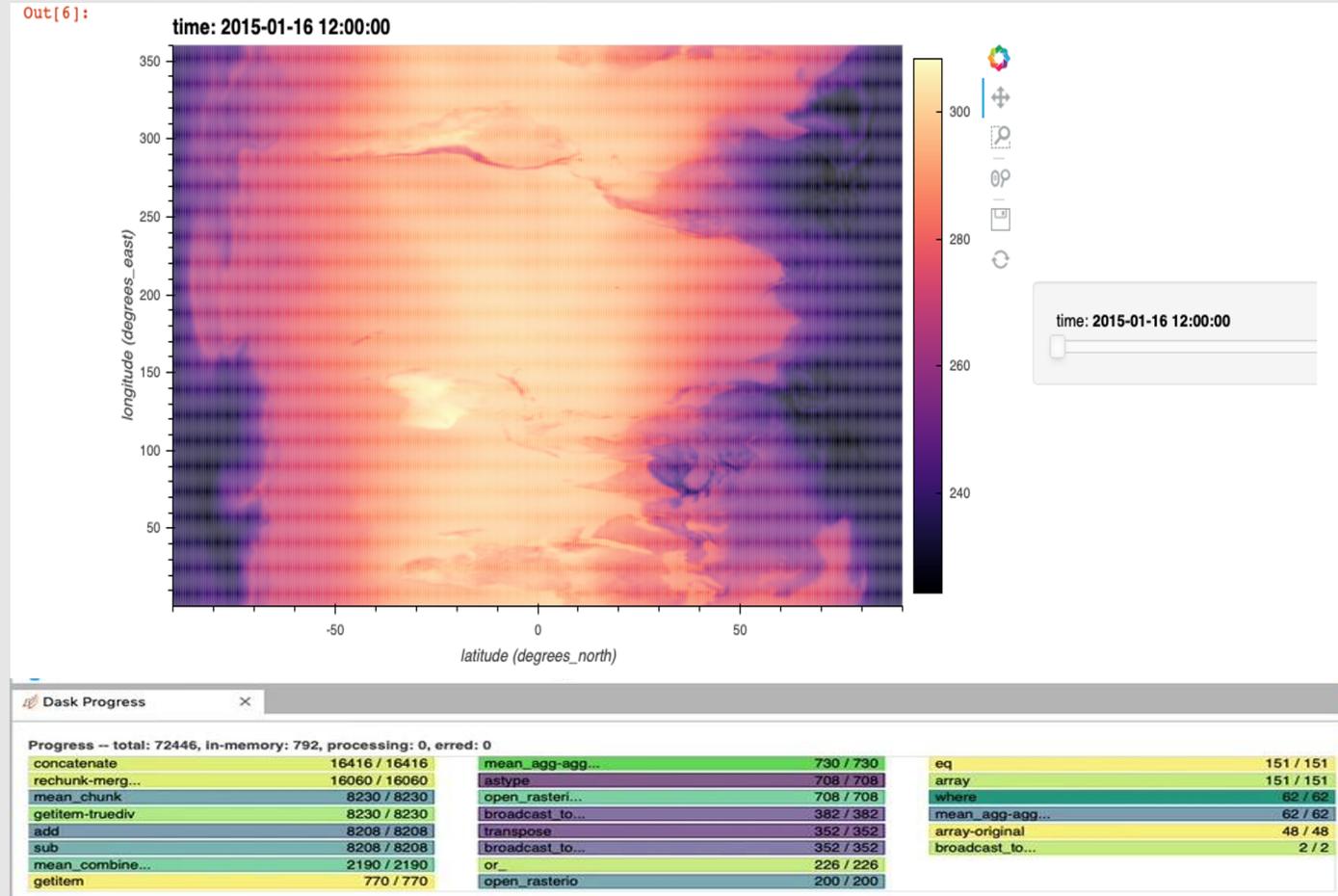
Interactivity



Distributed computing



Data models / numeric



PANGEO DEPLOYMENT AT GADI: AN ACCELERATION TOOL



Research use-cases

- Climate data analysis
- Weather data analysis
- Earth observation
- Geophysics
- Natural Hazards



Tech developments

- Libraries and Tools
- Interactivity
- Cloud/HPC infrastructure
- Direct data access

Pangeo – a big-data analysis platform at scale

Learning Goals for this presentation:

- Provide an overview of the Pangeo ecosystems
- Announce the data analysis environment
- Point to the documentation space
- Demonstrate data analysis examples

What is Pangeo?

“Pangeo is first and foremost a *community* promoting open, reproducible, and scalable science.” (<http://pangeo.io>)

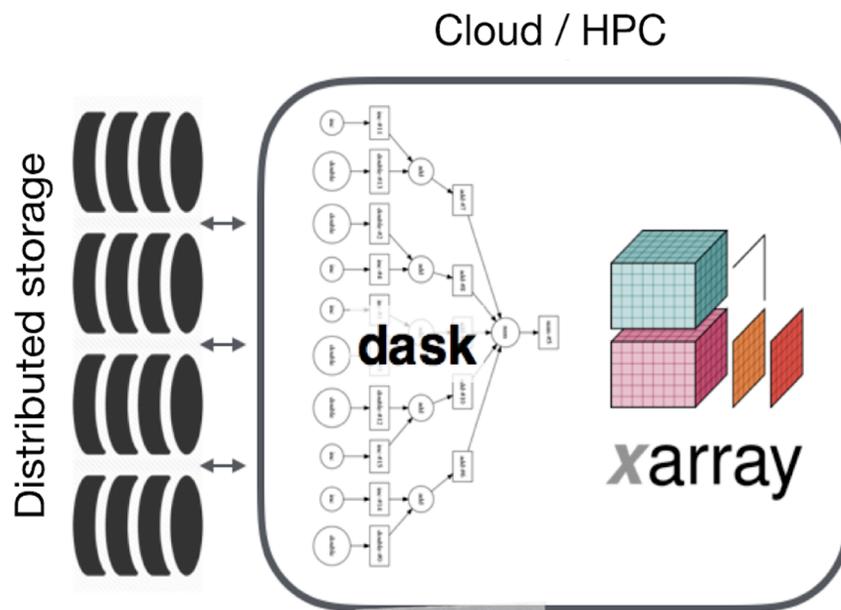


Why do we need Pangeo?

Need better tools to support exploration of increasingly large data volumes

PANGEO ARCHITECTURE

“Analysis Ready Data”
stored on globally-available
distributed storage.



Jupyter for interactive
access remote systems

end user

web browser

Xarray provides data structures
and intuitive interface for
interacting with datasets

Parallel computing system allows
users deploy clusters of compute
nodes for data processing.

Dask tells the nodes what to do.

(<http://pangeo.io>)

Step1: submit a job on Gadi to spin up a Jupyterlab server

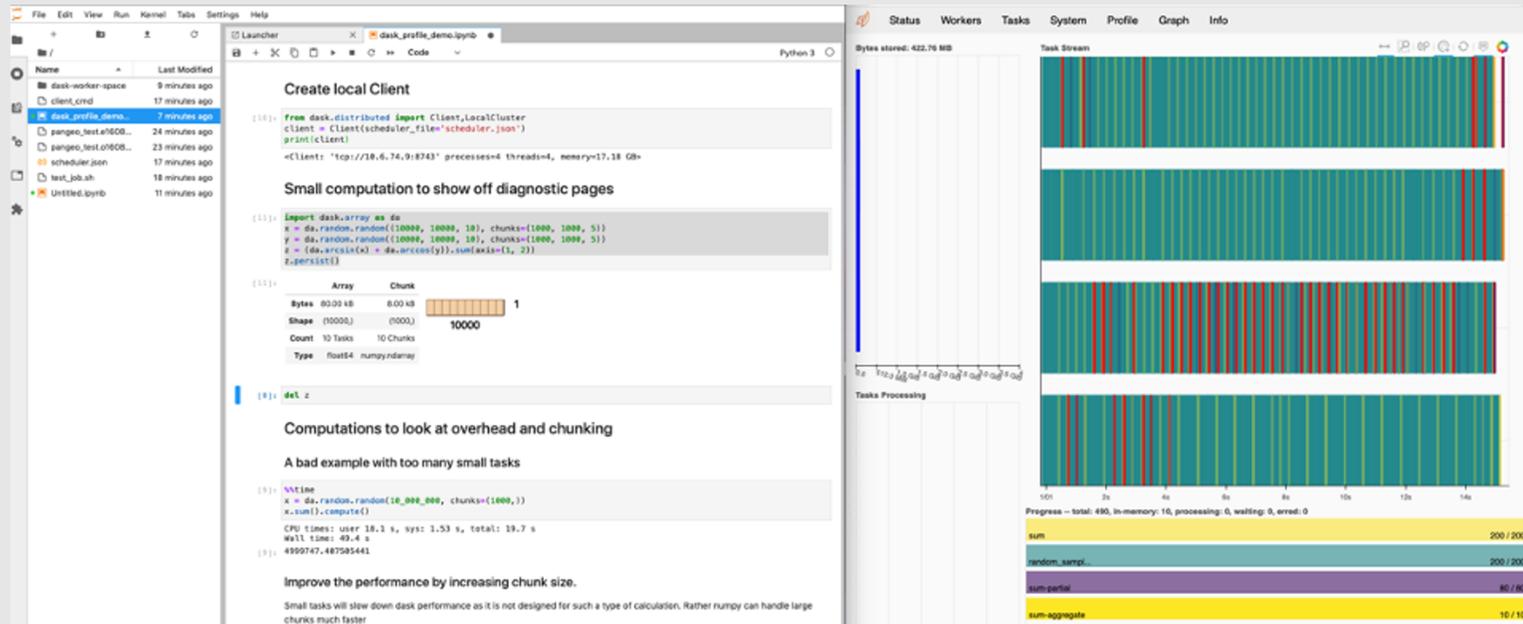
```
#!/bin/bash
#PBS -N pangeo_test
#PBS -P <project code>
#PBS -q normal
#PBS -l walltime=5:00:00
#PBS -l ncpus=96
#PBS -l mem=384GB
#PBS -l jobfs=100GB
#PBS -l storage=scratch/<project code>+gdata/<project code>
module use /g/data/dk92/apps/Modules/modulefiles
module load pangeo
module load NCI-data-analysis/2020.12
pangeo.ini.all.sh
sleep infinity
```

Step2: ssh Gadi and open the ports on web browser (two tabs)

```
$ ssh -N -L 8388:gadi-cpu-clx-2224.gadi.nci.org.au:8388 abc123@gadi.nci.org.au &
```



Step3: open the JupyterLab app and the dashboard



The image displays two side-by-side screenshots. The left screenshot shows a JupyterLab notebook with the following code:

```
from dask.distributed import Client, LocalCluster
client = Client(scheduler_file="scheduler.json")
print(client)

<Client: 'tcp://10.6.74.9:8743' processes=4 threads=4, memory=17.18 GB>

import dask.array as da
x = da.random.random(10000, 1000, 10), chunks=(1000, 1000, 5)
y = da.random.random(10000, 1000, 10), chunks=(1000, 1000, 5)
z = (da.arccos(x) - da.arccos(y)).sum(axis=(0, 2))
z.persist()

Array          Chunk
Bytes 8000 kb  8.00 kb  1
Shape (10000,) (1000,) 10000
Count 10 Tasks 10 Chunks
Type float64 numpy.ndarray

del z

Computations to look at overhead and chunking

A bad example with too many small tasks

%%time
x = da.random.random(10_000_000, chunks=(1000,))
x.sum().compute()

CPU Times: user 18.1 s, sys: 1.53 s, total: 19.7 s
Wall Time: 49.4 s
4999747-447585441

Improve the performance by increasing chunk size.
Small tasks will slow down dask performance as it is not designed for such a type of calculation. Rather numpy can handle large chunks much faster
```

The right screenshot shows the Dask dashboard. It features a 'Task Stream' visualization with a grid of colored bars representing tasks. Below the task stream, there are progress bars for various tasks, including 'sum', 'random_samp', 'sum-partic', and 'sum-aggregate'. The dashboard also shows 'Bytes stored: 422.76 MB' and 'Tasks Processing'.

Scalable –

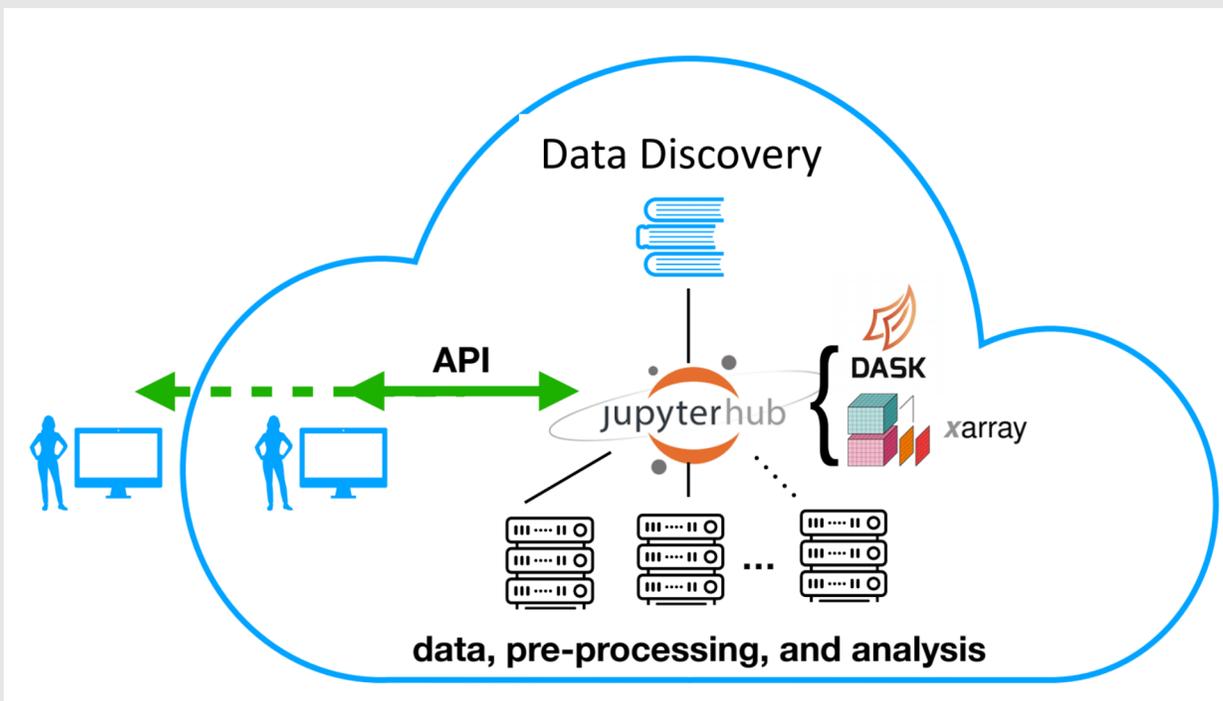
You can submit PBS jobs for the intensive compute parts of your workflow inside a notebook

```
import dask.config
from dask.distributed import Client, LocalCluster
from dask_jobqueue import PBSCluster
walltime = '01:00:00'
cores = 96
memory = '160GB'

cluster = PBSCluster(walltime=str(walltime), cores=cores, memory=str(memory),
                    job_extra=['-P <project code>', '-l ncpus='+str(cores), '-l mem='+str(memory),
                               '-l storage=gdata/<project code>+gdata/<project code>+gdata/<project code>...'],
                    header_skip=["select"], python=os.environ["DASK_PBS_PYTHON"])
cluster.scale(jobs=2)
client = Client(cluster)
client
```

Pangeo/Jupyter could be one of the essential interfaces to NCI's resources:

Move analysis to the data



Instant access to compute resources and data via PBS queueing system

Democratize access large computations accessed with web browser

No downloading data

Scalable computational power used and billed by time

On-demand special resources (GPUs)

Reproducible workflows thanks to network-accessible datasets and containerized software

(Credit: Scott Henderson, University of Washington)

Things to be mindful of when using Pangeo

As the compute nodes do not allow internet access, libraries that download things on the fly won't work. For example, Cartopy might need to download a coastline database. In this case, you need to download the database onto Gadi, then point to the access point in your workflow.

Balance the resources requested for serial or parallel jobs. You can manage this by requesting minimum resource to get Pangeo started, then submit computationally intensive jobs inside your workflow to set up a Dask cluster as needed.

Running notebooks on VDI vs using Pangeo on Gadi

Pangeo on Gadi can utilise Dask or xarray for parallel computing and data processing. However, this will likely require more resources such as CPU, memory and I/O throughput.

Note: Pangeo jobs should be submitted to the queue system and we recommend you request node-based resources.

Don't waste your SUs!

The NCI-provided Virtual Desktop Infrastructure (VDI) is useful for:

- executing lightweight, serial/parallel Jupyter notebooks or Python scripts without consuming SUs
- developing scripts for the Pangeo environment

For more information on the VDI, see <https://opus.nci.org.au/display/Help/VDI+User+Guide>

WHAT'S NEXT ?

- Deploy Pangeo on a Cloud infrastructure

Live demo

- How to set up Pangeo on Gadi

<https://opus.nci.org.au/display/Help/5.1+Set+up+Pangeo>

Step 1. Enabling Pangeo in your shell environment

To enable the Pangeo environment, you can use the following command within jobs, or within an interactive environment:

```
$ module load pangeo/<version>
```

```
Loading pangeo/2010.10
```

```
Loading requirement: intel-mkl/2019.3.199 python3/3.7.4 hdf5/1.10.5
```

```
netcdf/4.7.4
```

Step 2. Configure your account on Gadi (once-only)

JupyterLab is bundled within the Pangeo environment and will be used to load notebooks and monitor jobs. To set up this environment, run the following two commands:

```
$ jupyter notebook --generate-config
```

```
$ jupyter notebook password
```

This is a stand-alone password that you will use later for accessing the JupyterLab server. It has nothing to do with your NCI login account and password. You can use this command to reset your password at any time.

Step 3. Submitting a multi-node Pangeo job to Gadi

First create a directory where you will run the Jupyter notebook:

```
$ mkdir -p ~/pangeo/tutorial
```

Next you need to create a PBS shell script that will be used to launch a multi-node Pangeo job:

```
#!/bin/bash          ### see https://opus.nci.org.au/display/Help/PBS+Directives+Explained for explanation on PBS directives
#PBS -N pangeo_test
#PBS -P <project code>
#PBS -q normal      ### see https://opus.nci.org.au/display/Help/Queue+Limits for Gadi Queue Limits
#PBS -l walltime=5:00:00
#PBS -l ncpus=96
#PBS -l mem=384GB
#PBS -l jobfs=100GB
#PBS -l storage=scratch/<project code>+gdata/<project code>

module load pangeo
pangeo.ini.all.sh
sleep infinity
```

Step 3. Submitting a multi-node Pangeo job to Gadi

```
#!/bin/bash
#PBS -N pangeo_test
#PBS -P <project code>
#PBS -q normal
#PBS -l walltime=5:00:00
#PBS -l ncpus=96
#PBS -l mem=384GB
#PBS -l jobfs=100GB
#PBS -l storage=scratch/<project code>+gdata/<project code>

module load pangeo
pangeo.ini.all.sh
sleep infinity
```

Note that for Gadi, the “#PBS -l storage=” flag is required which must include **all** the scratch and gdata project IDs that will be used in your codes.

Dask requires whole nodes so jobs beyond a single node must use multiples of 48 for their ncpus request.

Step 3. Submitting a multi-node Pangeo job to Gadi

To submit the job to the queue:

```
$ qsub run_ipynb_job.sh
```

and take note of your `job_id` (which may look something like `1030967.gadi-pbs`).

Check to see when the job is running:

```
$ qstat <job_id>
```

Step 3. Submitting a multi-node Pangeo job to Gadi

To ease the user experience of software installation, NCI provides a versioned virtual environment which includes a number of Python packages for data processing and visualisation. They are managed within project dk92. To use this virtual environment:

```
$ module use /g/data/dk92/apps/Modules/modulefiles
```

```
$ module load NCI-data-analysis/2020.12
```

A combination of Pangeo and NCI data-analysis virtual environments reduces the hassle of installing software and solving dependencies, and provides an interactive working environment for using JupyterLab. To use both Pangeo and this virtual environment, just add the above two lines to your PBS job submission script.

Step 3. Submitting a multi-node Pangeo job to Gadi

```
#!/bin/bash
#PBS -N pangeo_test
#PBS -P <project code>
#PBS -q normal
#PBS -l walltime=5:00:00
#PBS -l ncpus=96
#PBS -l mem=384GB
#PBS -l jobfs=100GB
#PBS -l storage=scratch/<project code>+gdata/<project code>
```

```
module use /g/data/dk92/apps/Modules/modulefiles
module load pangeo
module load NCI-data-analysis/2020.12
pangeo.ini.all.sh
sleep infinity
```

Step 4. Set up port forwarding to access from your desktop machine

Once the job is running on Gadi, there will be two files that are created in your current Gadi directory:

- `cliend_cmd`
- `scheduler.json`

The file `client_cmd` contains commands to forward network traffic from the defined port number of the worker node to an external client machine (i.e., your desktop) via the login node `gadi.nci.org.au`

Step 4. Set up port forwarding to access from your desktop machine

Running:

```
$ more client_cmd
```

should give an output that looks something like:

```
ssh -N -L 8388:gadi-cpu-clx-2224.gadi.nci.org.au:8388 abc123@gadi.nci.org.au
```

```
ssh -N -L 8768:gadi-cpu-clx-2224.gadi.nci.org.au:8768 abc123@gadi.nci.org.au
```

For this example, JupyterLab uses port 8388 and Dask dashboard occupies port 8768 respectively from Gadi worker node gadi-cpu-clx-2224.

Note that both port numbers are randomly chosen for each job and will be different each time you run a new job.

Step 4. Set up port forwarding to access from your desktop machine

Next, on your remote machine (e.g., Desktop), run each of the following commands separately if you have already set up SSH keys:

```
$ ssh -N -L 8388:gadi-cpu-clx-2224.gadi.nci.org.au:8388 abc123@gadi.nci.org.au &
```

```
$ ssh -N -L 8768:gadi-cpu-clx-2224.gadi.nci.org.au:8768 abc123@gadi.nci.org.au &
```

If you haven't set up SSH keys, instructions on how to do this can be found at <https://opus.nci.org.au/display/Help/Using+SSH+keys>

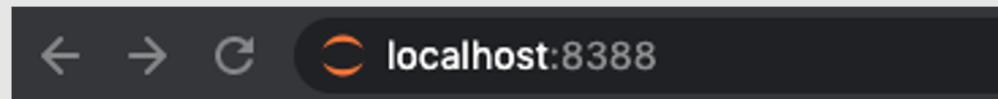
Alternatively, you should enter your Gadi password when prompted.

Step 5. Connect to the remote JupyterLab server from your remote desktop computer

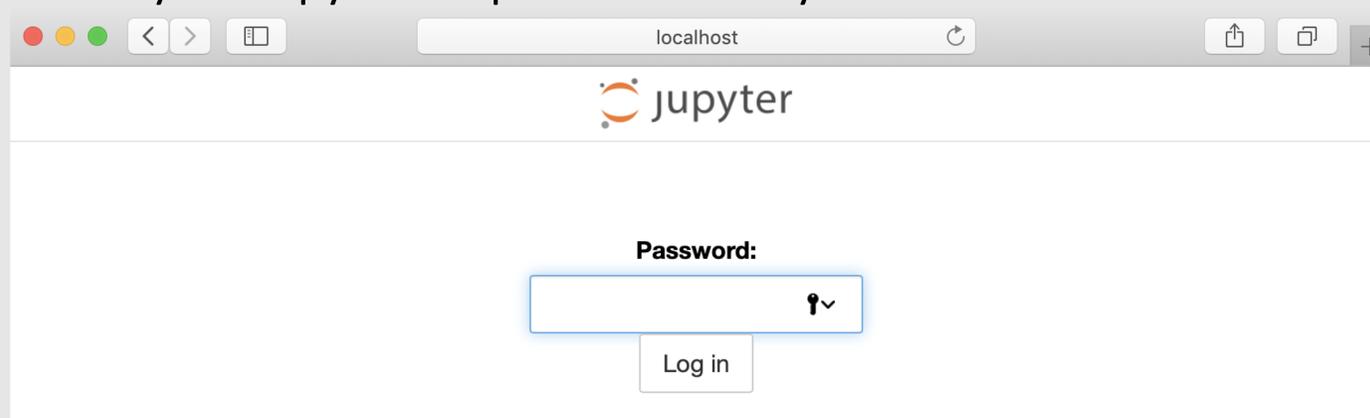
In a browser on your local desktop, type in the following URL:

“localhost:xxxx”

where xxxx is the port number from your client_cmd file

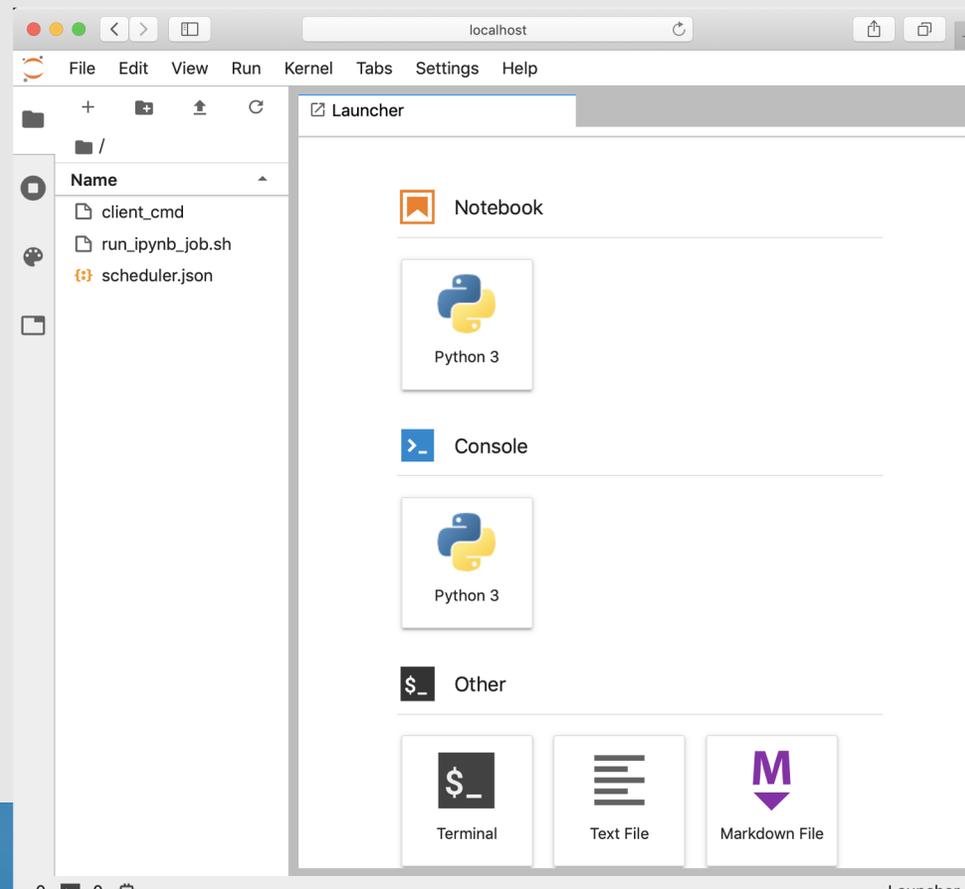


You will be prompted for your JupyterLab password that you created earlier:



Step 5. Connect to the remote JupyterLab server from your remote desktop computer

Once your authentication has passed, a JupyterLab interface will be launched in a few seconds:



Step 6. Importing a notebook example

You can drag and drop a notebook from your local machine into the JupyterLab. This file will also appear in your working directory on Gadi:

The screenshot illustrates the process of importing a notebook into JupyterLab. It is divided into three numbered sections:

- 1:** A local file explorer window shows a directory containing several files, including `annual_ave.ipynb`. A red box highlights this file, and a red arrow points to it.
- 2:** A yellow callout box with the text "Drag and drop from your local directory to JupyterLab" is positioned over the `annual_ave.ipynb` file in the local explorer. A red arrow points from this box to the file.
- 3:** A terminal window shows the output of a `ls -l` command in the remote Gadi environment. The output lists files in the current directory, and `annual_ave.ipynb` is highlighted with a red box. A yellow callout box with the text "When the notebook is dragged and dropped into the JupyterLab directory, the file appears in your Gadi working directory immediately." has a red arrow pointing to the highlighted file in the terminal output.

The central JupyterLab interface shows the notebook `annual_ave.ipynb` open in the Python 3 kernel. The code cells contain the following Python code:

```
[1]: import xarray as xr
      from pylab import *
      from datetime import *

[2]: from dask.distributed import Client, LocalCluster
      client = Client(scheduler_file='scheduler.json')
      client

Client                               Cluster
Scheduler: tcp://10.9.4.62:8729        Workers: 32
Dashboard: http://10.9.4.62:8891/status Cores: 32
                                        Memory: 67.42 GB

[3]: #source: https://github.com/COSIMA/ACCESS-OM2-1-025-010deg-report/blob/m
      def fixcicetime(da):
          ...
          Correct the time coordinate in DataArray from CICE netcdf file.
          CICE netcdf files unhelpfully have a time coordinate which is just a
          e.g. the time stamp for a January average is 1 February, which messe
          This function just subtracts 12 hours to put it in the correct month
          PR 109 gives an option to fix this:
          https://github.com/OceansAus/cosima-cookbook/pull/109
          ...
          try:
              da['time'] = da.time - timedelta64(12, 'h')
          except:
```

Step 7. Setting up your Jupyter notebook to use the Dask server

To use the dask server established from the PBS job, it is necessary to add and run the following cell at the beginning of your notebook:

```
from dask.distributed import Client, LocalCluster
client = Client(scheduler_file='scheduler.json')
print(client)
```

The output will show the configuration of the client and Dask cluster. You can check that the number of cores matches what you requested in the job script. Now you can run your notebook as per usual.

To gracefully stop the PBS job:

```
!pangeo.end.sh
```

Step 7. Setting up your Jupyter notebook to use the Dask server

View compute threads using Dask dashboard

From your local desktop, open a new tab in your web browser and type the second port in the client_cmd file to open the Dask dashboard (e.g. localhost:8768). This will allow you to see the dynamic resources of the processing.



```
[ccc777@raijin4 ccc777]$ more run_ipynb_job.sh
#!/bin/bash
#PBS -N pangeo_test
#PBS -P c25
#PBS -q express
#PBS -l walltime=5:00:00
#PBS -l ncpus=32
#PBS -l mem=64GB
#PBS -l jobfs=100GB
module load pangeo/2019.10
pangeo.ini.all.sh
sleep infinity
```

- Make sure your project has enough kSU allocated to complete the job
- For the queue selection (-q), *normal* is recommended if the job is not urgent
- *Walltime* provides the limit of the job run, so make sure you specify enough walltime to run a computationally expensive job
- Watch for the new version of Pangeo in three months time

Add these lines into your notebook or python script!!

```
# start the dask client
from dask.distributed import
Client, LocalCluster
client =
Client(scheduler_file='scheduler.json')

... your work utilizing xarray&dask

# stop the pbs job.
! pangeo.end.sh
```