Analysis of FastEddy® Model Data on GPUs

Shay Liu, NCAR CISL SIParCS 2020 intern

Mentors Supreeth Suresh and Cena Miller



NSF

July 29, 2020

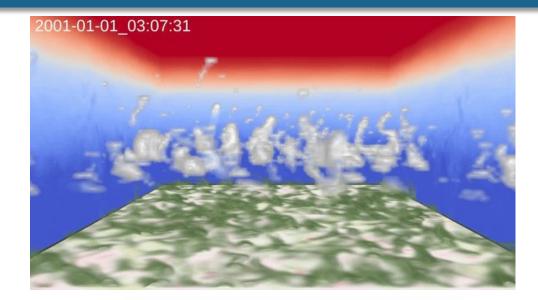
Outline

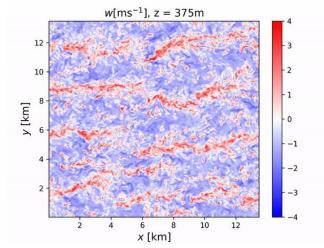
- Introduction
- Project goals
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- Single GPU data analysis
- Multi-node GPU data analysis
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Introduction

- Model analysis is traditionally done on CPUs
- Model analysis is often embarrassingly parallel and compute intensive
- These types of tasks are well suited for GPU acceleration
- FastEddy® is a GPU-based large eddy simulation (LES) model developed in RAL, which produces large datasets
- Using GPUs for *FastEddy*® analysis potentially reduces I/O and helps create a faster process of analysis for the science team



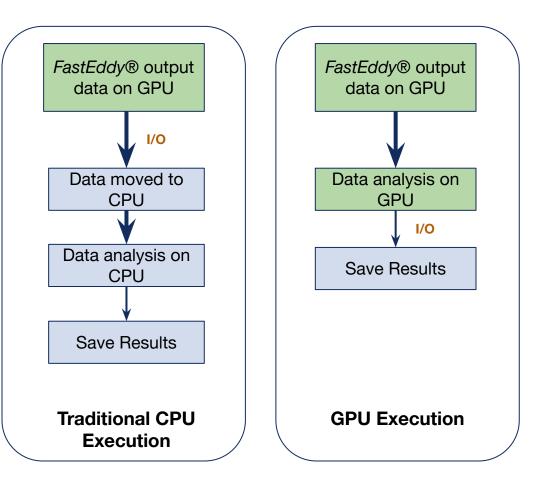


Video courtesy of Dr. Jeremy Sauer, NCAR RAL



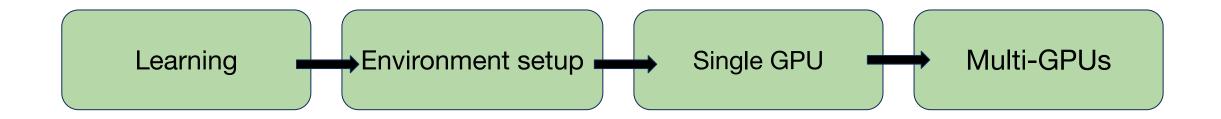
Project Goals

- 1. Become familiarized with the architecture of GPUs
- 2. Perform *FastEddy*® data analysis on GPUs
 - a. Single GPU execution
 - b. Multi-GPU execution
- 3. Prototype a simplified GPU acceleration of the data science phase
 - a. Accelerate data analysis on GPUs to match the high-speed data production on GPUs





Work Progress





Initial Setup

Learning

- NVIDIA Courses about RAPIDS
- Cupy, CuDF, CuGraph, and Dask

Setting up environment

- Conda environment
- Package installation
- JupyterLab extensions



Libraries

Cupy

- Cupy is a python library to do element-wise array operations on GPU
 - Analogous to numpy on CPU
- Cupy simplifies GPU acceleration process
- Cupy preserves data structures

Dask

- Dask schedules tasks for parallelism and distributes the workload for you
- Dask uses lazy evaluation and thus optimizes load and store of data
- Dask works with xarray, cupy, numpy, pandas, cudf, etc

JupyterLab

- JupyterLab is a web-based interactive development environment (IDE)
- JupyterLab supports dask lab extensions to monitor work processes









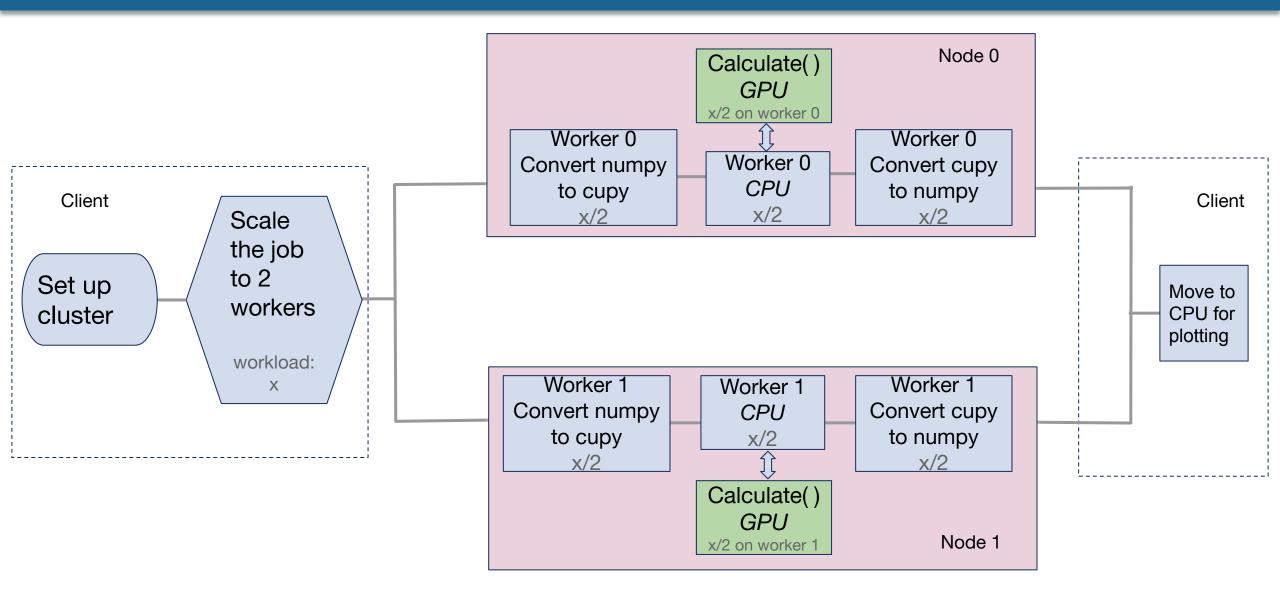
System Details

NCAR Casper Supercomputer

- Up to **384 GB** DDR4-2666 memory per node
- **2 18-core** 2.3-GHz Intel Xeon Gold 6140 (Skylake) processors per node
- 2 TB local NVMe Solid State Disk
- 1 Mellanox ConnectX-4 100Gb Ethernet connection (GLADE, Campaign Storage, external connectivity)
- 1 Mellanox ConnectX-6 HDR100 InfiniBand link
- **1 NVIDIA Quadro GP100 GPU 16GB** PCIe on each of 8 nodes



Dask Execution Workflow





Dask Working Example: Scheduler, Workers, & Delayed Objects

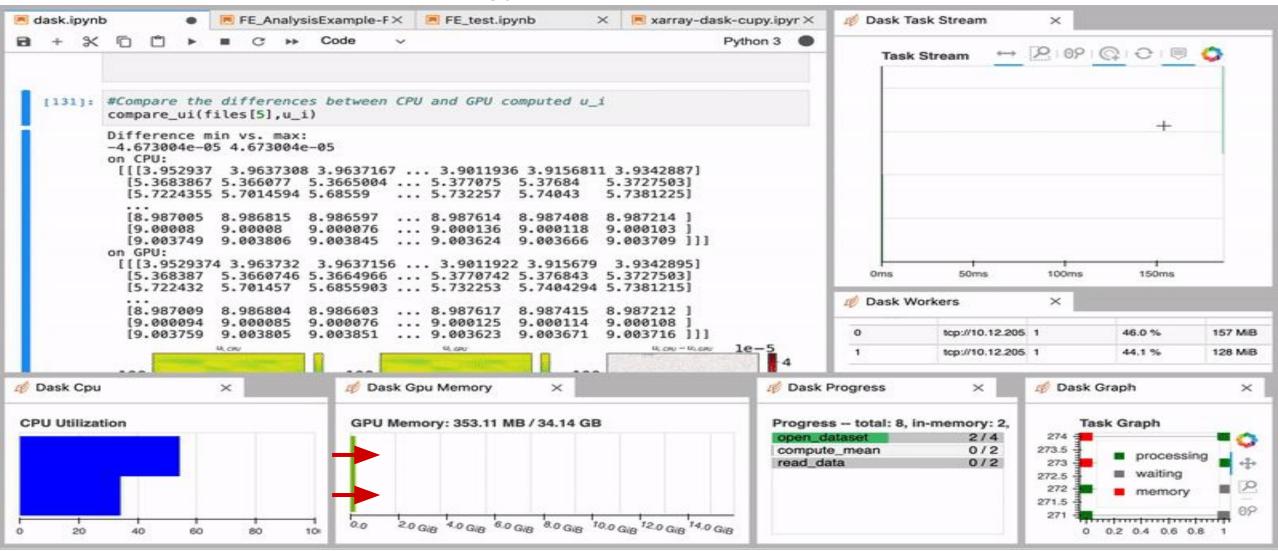
Request 2 computing nodes with 1 GPU each (inside a Jupyter session)

```
cluster = SLURMCluster(cores=1, processes=1, walltime='01:00:00',
                        scheduler options={"dashboard address" :'0.0.0.0'},
                        extra=['--resources GPU=1'],
                        job extra=['--constraint=gpu','--account=ntdd0002',
                        '--reservation=TDD 2xgp100', '--mem=0'],
                        env extra=['module load cuda/10.1',])
client = Client(cluster)
cluster.scale(2)
!squeue -u $USER -1
                                                                         @dask.delayed
                                                                         def my func(filepath):
Mon Jul 20 17:53:42 2020
                                                                              x = cupy.array(y)
     JOBID PARTITION
                   NAME USER STATE TIME TIME LIMI NODES
                                                                              return(x)
NODELIST(REASON)
                   dask-wor xuecliu RUNNING
                                         0:02 1:00:00
                                                     1 casper06
    5614085
            dav
                                         0:02 1:00:00
    5614086
            dav
                   dask-wor xuecliu RUNNING
                                                    1 casper07
                                                                         results = my func(filepath)
    5613902
           dav
                          xuecliu RUNNING 37:33 6:00:00
                                                    1 casper23
                   srun
                                                                         x = results.compute()
```



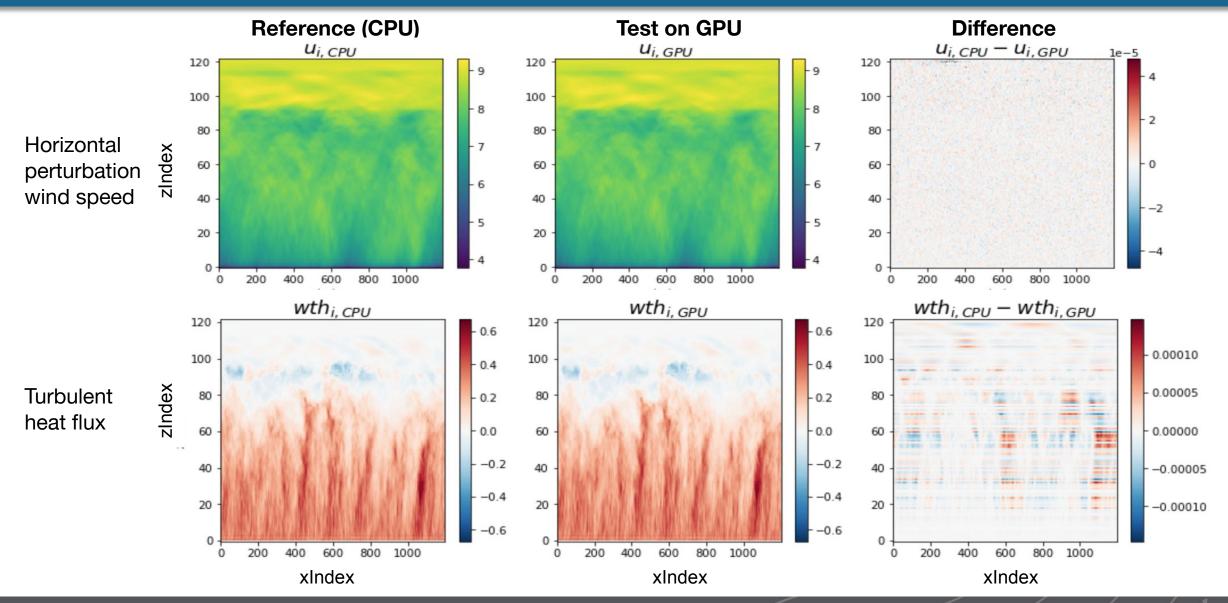
Monitor Work with Dask Graphic Extensions

Dask-labextension + nvdashboard in a JupyterLab session



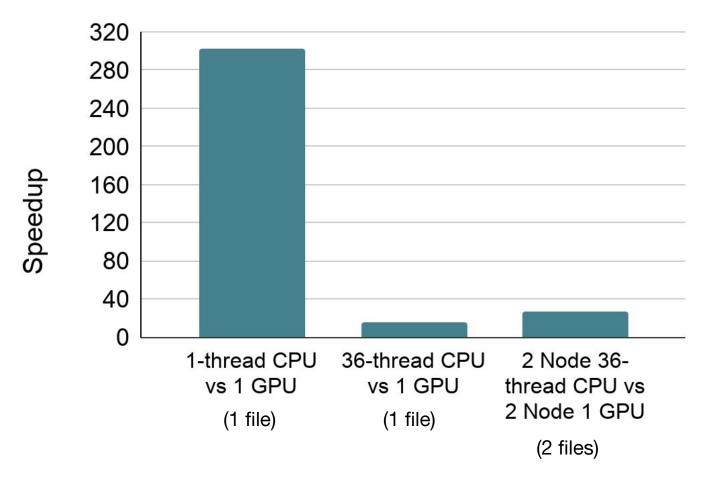


Validation





Results



- Speedup for analysis of a single file:
 - 302x for 1-thread CPU vs. 1 GPU
 - 15.3x for 36-thread CPU vs. 1 GPU
- Speedup for analysis of two files:
 - 26.3x for 2 nodes, 36-thread CPU vs.
 2 nodes with 1 GPU on each node



Summary and Future Work

Summary

- Cupy significantly improves and simplifies the process of GPU acceleration for data analysis
- Dask + cupy together facilitate data analysis on multi-GPUs

Future work

 Incorporate an in-situ GPU acceleration workflow in FastEddy®



Acknowledgements

Technical & Scientific Support

- Anderson Banihirwe, NCAR CISL
- Mick Coady, NCAR CISL
- Dr. Raghu Raj Kumar, NVIDIA
- Dr. Richard Loft, NCAR CISL
- Dr. Jeremy Sauer, NCAR RAL

Administrative Support

- AJ Lauer, NCAR CODE
- Virginia Do, NCAR CODE
- Jerry Cyccone, NCAR Education & Outreach
- Jess Hoopengardner, NCAR CODE



Thank you.

Questions?

