TECA: A Parallel Toolkit for Extreme Climate Analysis

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Abstract

We present TECA, a parallel toolkit for detecting extreme events in large climate datasets. Modern climate datasets expose parallelism across a number of dimensions: spatial locations, timesteps and ensemble members. We design TECA to exploit these modes of parallelism and demonstrate a prototype implementation for detecting and tracking three classes of extreme events: tropical cyclones, extra-tropical cyclones and atmospheric rivers. We process a modern TB-sized CAM5 simulation dataset with TECA, and demonstrate good runtime performance for the three case studies.

Keywords:
Feature Detection and Tracking, Parallel Analysis, Climate Analysis

1. Introduction

Modern climate simulations produce massive amounts of data. Commonly used models such as the Community Earth System Model (CESM) and Weather Research and Forecasting model (WRF) routinely produce tens of GBs of data. Next generation Global cloud resolving simulations will soon produce TBs of data on a per-timestep basis. Coordinated multi-model ensembles of climate model simulations such as the Coupled Model Intercomparison Project (CMIP3) [1] contain hundreds of GBs today, CMIP5 [2] will contain tens of TBs in the near future. Such datasets have presented tremendous opportunities in terms of sophisticated analysis (time-series, geo-spatial, pattern detection, etc.) to further our understanding of the climate system. Indeed such ensembles are a crucial tool for international and national organizations, such as the Intergovernmental Panel on Climate Change (IPCC), tasked to assess the human role in climate change and the potential of adaptation and mitigation strategies.

While valuable insight has been gained from such datasets, the sheer size of the CMIP3 archive has present significant challenges to the climate science community. The increased magnitude of CMIP5 in terms of both data volume as well as complexity is limiting it potential uses. Conventional visualization and analysis tools, such as CDAT [3], ferret [4], and nco [5], continue to rely on a serial execution model, fundamentally limiting the applicability of such tools to large datasets. As higher resolution climate models enter the mainstream, insurmountable obstacles will face the climate community if these limitations are not removed. While efforts, such as UV-CDAT [6], ParCAL [7] and PAGODA [8] are currently underway, advanced capabilities, such as machine learning and spatio-temporal analysis,

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remain out of reach for most tools. Such limitations on the ability of climate scientists to exploit these large datasets are unnecessary, as large supercomputing systems and commodity clusters are now commonly available and provide ample horsepower to facilitate sophisticated analysis. In this work, we build on current parallel computing hardware and distributed memory programming models to develop capabilities for analyzing modern massive climate datasets.

Climate model output exposes ample parallelism across multiple dimensions. Typically, it is possible to run the analysis code across individual ensemble members, timesteps, spatial regions and individual grid points. For instance, hurricane detection can be performed independently across models with perturbed physics (ensembles), years, spatial regions (northern hemisphere vs. southern hemisphere) and grid locations. Therefore, it is imperative that we design and develop analysis capabilities that exploit the high degree of parallelism in climate datasets, and overcome the large data challenges in the climate community.

TECA (Toolkit for Extreme Climate Analysis) is our first step in this direction. We are interested in the characterization of extreme climate events (tropical cyclones, extra-tropical cyclones, atmospheric rivers, etc.). While these specific events may be characterized by different features (which we discuss Section 3), we note that the majority of the runtime is dominated by the feature detection step, which can exploit temporal and spatial parallelism to good effect. Moreover, the specifics of implementing these flavors of parallelism are independent of the feature in consideration; therefore, we designed TECA to do the heavy lifting in terms of loading data and providing spatial/temporal parallelism, allowing developers to concentrate on implementing the particulars for each feature/event type.

To summarize, we prescribed the following design goals for TECA:

- The toolkit should provide support for spatial and temporal parallelism
- It should be easy to create an end-to-end custom analysis application
- It should be easy to add new feature detection algorithms
- The toolkit should provide climate-specific convenience functions, e.g., for loading NetCDF files, supporting calendars, etc.

We have achieved a number of these goals in the current TECA implementation. In the following we first discuss the TECA software design (Section 2) and present three use cases that illustrate the toolkit in action (Section 3). We present related work and discuss the current state of TECA and avenues for future work in Sections 4 and 5, respectively.

2. TECA Software Design

As outlined in the previous section, our design goal for TECA was to design a general framework for handling various flavors of data parallelism (spatial, temporal) and to implement common features required by every feature tracking/detection algorithm (e.g. loading NetCDF files, handling multiple calendaring systems, etc). We designed and implemented TECA in C++; the distributed features were implemented using MPI.

From the perspective of a developer who wants to implement a new feature detection and tracking algorithm in TECA, he/she needs to be able to specify a sequence of tasks and the input (data) and output (results) to/from the task. Within a task, the developer has access to a 1D/2D/3D sub-block of data, and can implement the particulars of the feature detection technique. Note that the developer does not make distributed MPI calls, nor does he/she have to be bogged down with details of how the data was made available to the tasks. All he/she has to do is to iterate over their local sub-block and process the data.

Results of the detection technique are typically stored in a local table, which can be subsequently aggregated to a global table on a serial post-processing task. The developer writes custom code to analyze the contents of the table and generate the final results (statistics, tracks, etc).

We now examine the specifics of the TECA software design illustrated by Figure 1:

- Custom analysis tasks, such as feature detection and trajectory analysis, can be developed by inheriting from *TECA_base_task*. To interface the analysis with TECA and to define the data exchanged between consecutive analysis tasks, the developer needs to implement three virtual functions of *TECA_base_task* to: i) prepare the input data, ii) analyze the input data, and iii) prepare the output data. To ease parallelization of the analysis, TECA already provides a set of derived standard task-types (e.g., *TECA_base_filetask*), which implement the splitting of the analysis into subtasks.

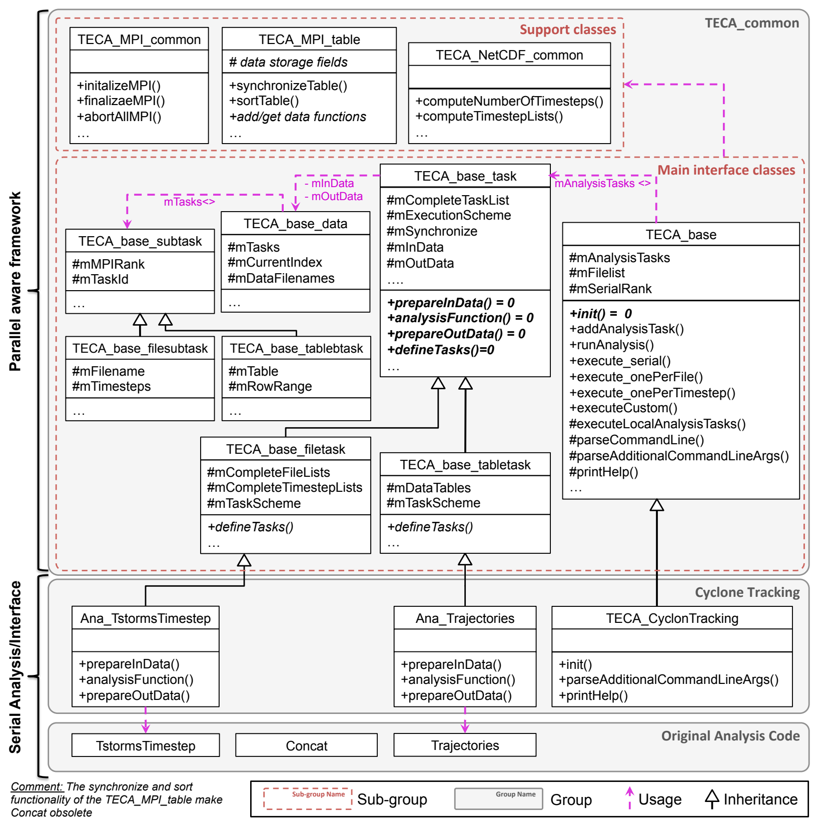


Figure 1: Class diagram of TECA and illustration of a parallel implementation of the tropical cyclone detection.

- Each task has access to local data via *TECA_base_data*, this includes information about local subtasks as well associated user data. *TECA_base_data* is used to specify the input and output of an analysis task.
- Output from each task is typically written to *TECA_MPI_table*. *TECA_MPI_table* implements a general distributed data table, which allows subtasks to store their results —such as cyclone locations— to the table while the table provides functionality for synchronization of the table data (i.e., gather/collect the data across MPI tasks) as well as for sorting the data records according to a user-defined subset of data dimensions (columns), e.g., yy:mm:dd. The structure of the table is defined by the application code itself. A column can be added to the table via a simple function call specifying the name and data type (e.g. double, int, char) for the new column. To populate the table with data, *TECA_MPI_table* provides *addRow*(...) and *setItem*(...) functions to create new data records and to define the value for a particular data item, respectively.
- A custom application is designed by inheriting from *TECA_base* and specifying a series of tasks, and their serial or parallel execution modes.

This design provides flexibility to the developer in implementing the serial analysis code independent of TECA, and then parallelizing the analysis by defining simple *TECA_base_task* wrappers. This approach can be readily utilized for porting existing serial analysis applications to parallel platforms. At the same time, a developer can easily implement new analysis methods directly in TECA with minimal overhead. Consequently, developers can better focus on the analysis problem at hand while TECA manages aspects of parallelization, data aggregation and chaining multiple analysis tasks in a pipelined fashion.

In the current implementation, TECA enables task classes to natively support parallelization over time (file+timestep) and data records (rows) of a data table. While it is preferable to have a 1-1 mapping between processing cores and timesteps, TECA enables users to process an arbitrary number of timesteps on each processing core. In the future, we plan to enable task classes to support spatial and spatio-temporal parallelism in addition. Currently, interfaces for loading NetCDF metadata are provided, but individual tasks make I/O calls on their own; we will address this in the future.

3. Application Case Studies

We now apply the TECA framework for three large scale climate analysis problems, namely those of automatically detecting and tracking tropical cyclones, extra-tropical cyclones, and atmospheric rivers in climate model output. The goal of the analysis is to characterize frequency and distribution of these important extreme events. The results of such analysis is useful for validating the accuracy of climate models in reproducing these events and investigating the changes in such events under different future scenarios.

All three case studies process high frequency output data from the Community Atmospheric Model (CAM5.1) at 0.25 degree resolution or approximately 28km at the equator. Data is stored at a temporal frequency of 3-hours. Eight time steps, corresponding to a single day, are stored in individual NetCDF files. The typical size of a single NetCDF file is 430MB; a year corresponds to roughly 156GB. The entire simulation output available to us is 4.2TB in size and corresponds to 27 simulated years (1979-2005). However, not all of the data is read and processed by different analysis problems. All analysis is performed on hopper, a Cray XE6 system at NERSC. Each node of the hopper system consists of 24 AMD cores with 32GB of memory. The system uses a Seastar network as the communication interconnect, and a lustre filesystem for parallel I/O. We use a simple file-per-process I/O strategy for the reading stage.

3.1. Tropical Cyclones

3.1.1. Scientific Motivation

Tropical storms are one of the most damaging climate events in terms of monetary destruction and loss of human life [9]. Better understanding of the future trend of frequency and severity of the tropical storms is critical to assessing impacts of climate change. High resolution climate models run under different scenarios of human activity provide a tool to project these trends [9, 10, 11]. These models are tested by performing simulations of the recent past, so their output can be compared against available observations. After assessing a model against these observations, they are run far into the future to investigate how tropical storm characteristics might change.

3.1.2. Algorithm

We begin our investigation by considering the TSTORMS code, originally developed at the Geophysical Fluid Dynamics Library [11] for detecting tropical storms. The TSTORMS code is representative of many such climate analysis programs: it processes climate model output one time step at a time, reads a handful of variables from the modeling output and then performs a series of computations to produce a relatively small set of candidate points. The detection step requires the majority of the computation time, and is characterized by the following conditions outlined in [11]:

1. **Vortex** is defined as the local relative vorticity maximum at the 850 hPa pressure isosurface. To be considered as a tropical storm, the maximum vorticity must exceed $1.6 \times 10^{-4}\text{s}^{-1}$, where the vorticity is the curl of wind velocity, and s denotes time in seconds.
2. **Low pressure core** is defined as a local minimum of the sea surface pressure. From the low pressure core outward, the surface pressure must increase by at least 4 hPa within a radius of 5 degrees. The local pressure minimum must be within a distance of 2 degrees latitude and longitude from the vorticity maximum. This pressure minimum is generally regarded as the storm center.
3. **Warm-core** is a local maximum of average temperature between 300 and 500 hPa. From the center of the warm-core outward, the temperature must decrease by at least 0.8 degrees Celsius in all directions within a distance of 5 degrees. The distance of the warm-core center from the storm center may not exceed 2 degrees.

All grid points that satisfy these multi-variate conditions form candidates for the next processing step. A stitching phase is now invoked, which essentially places spatio-temporal constraints involving the speed of tropical storms, the tendency to move poleward and westward and a specified minimum temporal duration. Such criteria are used to assign candidate points to individual tracks and resolve ties. The final output are individual storm tracks which can

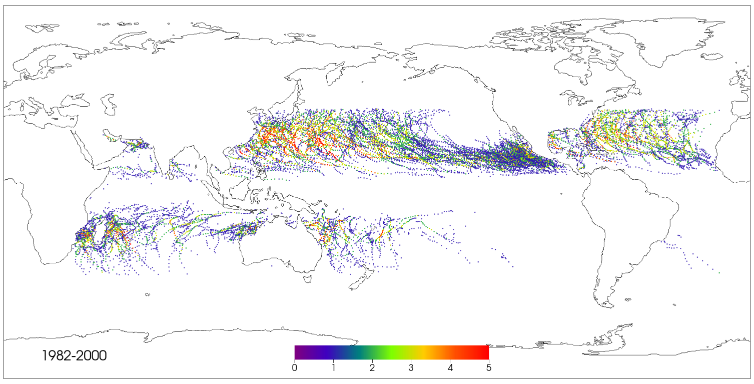


Figure 2: Tropical cyclone tracks for 19 years of CAM5 output. Tracks are colored by storm categories on the Sapphir-Simpson scale. Results were obtained by applying the parallel tropical cyclone analysis.

then be counted and categorized based on maximum wind speed. Note that the computationally expensive detection step is embarrassingly parallel across timesteps. The stitching step is harder to parallelize, but takes up little runtime, permitting execution in a serial mode.

The original TSTORMS is a single thread sequential program written in Fortran 77. It is fairly compute intensive: serial execution on 500GB of modeling output took many days [12]. Doubling the horizontal resolution causes the detection step to require 16 times more computations. In this work, we have re-implemented the tropical storm detection algorithm in C and integrated the tropical storm detection capability into the proposed TECA toolkit.

3.1.3. TECA integration

The design of the implementation of the cyclone detection analysis using TECA is illustrated in Figure 1. The initial detection of tropical storms at a single timestep is implemented in $Ana\_TstormsTimestep$. The storm detection is automatically split by TECA into concurrent subtasks, each of which processes one timestep. The computation of storm trajectories is then implemented as a serial task which operates on the $TECA\_MPI\_table$ data table generated by the storm detection.

Only minimal changes to the original analysis code are needed in order to integrate the analysis with TECA. The base analysis consists of three separate applications —TstormsTimestep, Concat, and Trajectories— which interact through the use of intermediate files. A preliminary implementation in TECA —which preserved the communication between tasks via intermediate files— did not require any changes to the original analysis code. The implementation described here required only few changes to the analysis code to allow the storm detection (TstormsTimestep) to output its results to a $TECA\_MPI\_table$ and enable the trajectories analysis (Trajectories) to operate on the table. Using $TECA\_MPI\_table$ for data exchange made the Concat step obsolete and removed the need for intermediate files for data exchange.

Integration of the tropical cyclone detection with TECA required implementation of the following main user code. For each main analysis task we defined a corresponding task class in TECA. The task classes implement the preparation of input and output data while using the original analysis code to perform the analysis task. In addition, the task classes specify how TECA should decompose the task into subtasks and how these subtasks should be executed. The main application class $TECA\_CycloneTracking$ (which inherits from $TECA\_base$), then links the different analysis tasks together to define a single coherent application. Here we mainly need to implement the *init*() function, which instantiates the different analysis tasks and adds them to the analysis pipeline.

3.1.4. Results

We processed 19 years of CAM5 output (1982-2000) with the tropical cyclone detection code. Data corresponding to the various fields used in the analysis amounted to $\approx$ 200GB in size. A plot of the resulting Category 1-5 trajectories is shown in Figure 2. We ran the detection step on 6935 cores of the hopper Cray XE6 system at NERSC. The detection step was completed in $\approx$ 2 hours. The results of the detection step was processed by the serial trajectory stitching step,

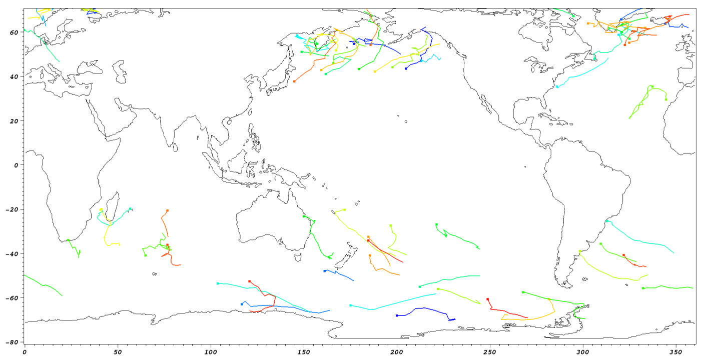


Figure 3: Snapshot of Extra-Tropical cyclone tracks for the month of January 2000. Tracks are colored based on individual storm systems. Results were obtained by applying the parallel extra-tropical cyclone analysis.

which took ≈ 10 seconds. This result highlights the power of data parallel computing: a task that would take ≈ 583 days to run on completion on a single core can now be completed in a few hours.

3.2. Extra-Tropical Cyclones

3.2.1. Scientific Motivation

Extra-tropical cyclones are of key importance to the climate at middle to high latitude regions. They determine the local weather systems and also have strong influence on the general circulation [13, 14, 15]. For instance, the traveling directions of Atlantic cyclones have been shown to determine the precipitation and temperature in northwestern and southern Europe [16]. Extra-tropical cyclones are characterized by lower winds and less intense pressure minima than their tropical counterparts, nevertheless they often result in heavy gales, thunderstorms and other severe weather. They are also generally much larger in their geographical extent than tropical storms and occur more frequently. A good understanding of how the statistics of extra-tropical cyclones (intensity, frequency, or position) change with the changing climate will be fundamental for the projection of the local climate in the middle to high latitude regions.

3.2.2. Algorithm

Our extra-tropical cyclone detection procedure is similar in spirit to cyclone detection albeit with a few differences. We follow the approach of [13, 17] for the extra-tropical cyclone detection and tracking procedure:

1. **Vortex** is defined as the local relative vorticity maximum at the 850 hPa pressure isosurface. A region of 200km × 200km is considered for determining the vorticity minima.
2. **Storm center** is defined as a closest pressure minimum within a 5 degree radius of the vortex.

A stitching step is then invoked on candidate points that satisfy these criteria. The extra-tropical storm is constrained to last for at least 2 days and travel at least 1000Km over the course of its duration. A maximum distance constraint of 600km is applied for every 6-hour interval, and a preference is given to storms that travel poleward and eastward during the trajectory creation process. Similar to the tropical cyclone analysis, we found that the detection step was the most expensive.

3.2.3. TECA Integration

The fundamental structure of the extra-tropical cyclone detection analysis is similar to the tropical cyclone detection discussed in Section 3.1. The design of the implementation of both algorithms in TECA as well as the effort required for integrating the analysis with TECA are comparable (see Section 3.1.3 and Figure 1).

3.2.4. Results

We processed 16 years of CAM5 output (1991-2005) with the extra-tropical cyclone detection code. Figure 3 shows sample trajectories from a single month in that duration. The processing was completed in ≈ 6 hours on 5840 cores. The larger runtime, especially compared to the tropical cyclones, is due to the wider latitude band that much be searched for these storms, typically 20N through 90N and 20S to 90S, as compared to 30N to 30S for tropical cyclones. We note that a single core would take ≈ 1460 days to analyze the same dataset.

3.3. Atmospheric Rivers

3.3.1. Scientific Motivation

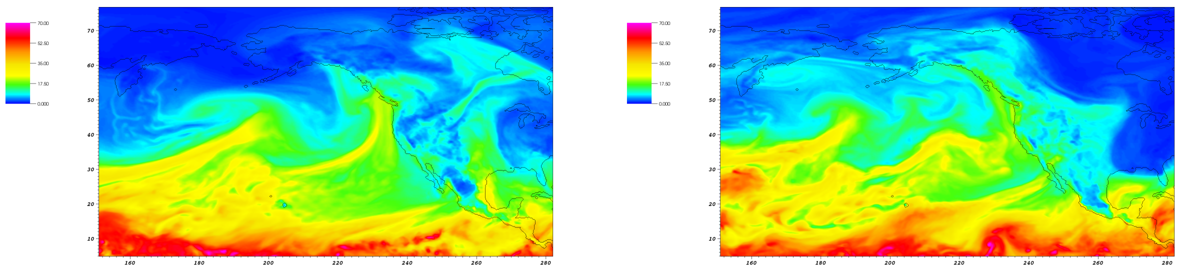
Extreme precipitation events on the western coast of North America are often traced to an unusual weather phenomenon known as atmospheric rivers (ARs). These events refer to long and narrow structures in the lower atmosphere that transports tropical moisture to the far-flung regions outside of the tropical zone [18, 19]. In one of the earliest studies on this phenomenon, it was determined that such a structure could carry more water than the great river Amazon [20, 21]. As they can be highly localized, *river* is an apt description of such a narrow stream of moisture moving at high speeds across thousands of kilometers. AR events occur in oceans around the globe, including the Atlantic basin affecting the British Isles.

The key characteristic recognized in earlier studies of ARs is the moisture flux [22]. However, that quantity turns out to be difficult to observe directly. In 2004, Ralph et al. [23] established a much simpler set of conditions to identify atmospheric rivers in satellite observations. Their detection is primarily based on the total column Integrated Water Vapor (IWV) content, which is measured in millimeters (mm) or centimeters (cm). They identify an AR as atmospheric feature with $IWV > 2cm$, more than 2000 km in length, and less than 1000 km in width. Satellite observations can direction measure IWV, however, the water vapor concentration in the model output files has to be vertically integrated in order to produce IWV. Some specific implementation details are as follows:

3.3.2. Algorithm

The AR detection process has two phases: i) detection of AR events and ii) computation of AR statistics. The first phase of our detection algorithm proceeds in four steps:

- The first step reads IWV data from a list of files. For climate model output, daily averaged values are read and then converted to three day averages.
- For a selected ocean basin, such as the northern Pacific Basin, select all mesh points where IWV is above a specified threshold value. Our default threshold is 2cm of equivalent water as suggested by Ralph at al. [23]. This step focuses our attention to a specific ocean basin. We also remove the tropical portion of the basin as our attention is focused on the extra-tropical features.
- Group the connected mesh points into regions in space through a connected component labeling algorithm. In this process, we count each mesh point as connected to eight neighboring points adjacent to it. We use a two-pass algorithm that gathers the connectivity information among the foreground pixels and then assign the final labels to each pixel [24]. The connectivity information is efficiently represented in a union-find data structure, which is known to be theoretically optimal in computational complexity measures. We refer to each connected region as a candidate.
- For each candidate, we verify the criteria suggested by Ralph et al. to classify it as an atmospheric river or not. We first verify whether a connected region originates from the tropical area and makes landfall on an appropriate coast. In the case of north Pacific basin, this would be the west coast of North America from California to British Columbia. If these two conditions are met, then we measure the length and the width for the region. The length is measured as the maximum length of the median axis of the region and the width is computed as the ratio between the area covered by the connected region and its length. A candidate satisfying the length and width constraints is classified as an Atmospheric River. If the event passes over Hawaii, it is further denoted as a ”Pineapple Express”. To evaluate the strength or other impacts, we compute quantities from additional model output fields such as precipitation, wind speed, moisture flux at landfall and so on.



(a) (b)

Figure 4: Sample CAM5 AR detections from our parallel code. Atmospheric rivers events in February and December of 1991 are plotted. Note that our method is able to detect AR events of different shapes and sizes.

3.3.3. *TECA Integration*

A standalone implementation of the above algorithm was presented in [25]. In this work, we enhance the implementation by integrating it into the TECA framework. In particular, TECA is able to handle the tasks of spatio-temporal parallelism. After the candidate points satisfy the AR criterion, the date, length, width, and landfall information is stored using *TECA_MPI_table*. The AR detection is implemented as a derived class of *TECA_base_filetask*. For each timestep of the data, a corresponding subtask is generated, while additional "ghost" timesteps may be included in each subtask to perform AR detection using, e.g, 3-day averages. Each of the subtasks is executed by TECA in parallel using a static scheduling scheme. Once the detection is complete, the output data of all subtasks is collected and sorted by date (yy:mm:dd) using the synchronize and sort functionality provided by *TECA_MPI_table*.

The second phase of the analysis takes the data table of the detected AR events as input and computes the AR event statistics, such as: i) the number of AR events in a year, ii) the length of each event, and iii) where each event land falls. This phase of the analysis is implemented as derived class of *TECA_base_tabletask*. Computing event statistics is inexpensive and is, therefore, executed by TECA as a single serial task. To link the two analysis tasks to a single coherent application, we then need to implement the main application class (which inherits from *TECA_base*) to define the overall analysis pipeline. The implementation effort and modifications required to the original analysis code are comparable to the storm detection (Section 3.1.3).

3.3.4. *Results*

We processed 27 years of CAM5 data (1979-2005) with the atmospheric river detection tool. The data corresponding to the integrated water vapor field is 32.5GB in size. Figure 4 shows two AR events in February and December of 1991 detected using our tool. We ran the detection step on 9,855 cores of the Hopper system in $\approx$ 4 seconds. If this step were run sequentially, the same detection code would have taken $\approx$ 657 minutes. The TECA code preserves the data parallelism we have shown in our standalone AR detection tool. The post-processing step to determine AR statistics ran on a single core of an XE6 node on the Hopper machine, taking $\approx$ 0.5 seconds.

4. Related Work

Climate scientists typically develop specialized data analysis tools for their research problems. The tropical storm detection code [11] and the atmospheric river detection code [19, 25] mentioned earlier belong to this category. The work presented in this paper attempts to develop a parallel framework for different analysis codes to work together on top of a common substrate that can handle flavors of spatial and temporal parallelism.

There have been a number of efforts to develop more generic climate analysis tools. We review a number of existing software packages contrast them with our present work.

CDAT *Climate Data Analysis Tool* is powerful suite of analysis and visualization capabilities targeted for the climate community. Its stated goal is to use an open-source, object-oriented, easy-to-learn scripting language (Python) to link together separate software subsystems and packages to form an integrated environment for data analysis. The tool is well designed and has a large number of users. However, we believe that their approach does not emphasize the need for parallel data analysis. We also note that the the next generation UV-CDAT [6] infrastructure is trying to address some of these limitations.

GrADS (Grid Analysis and Display System) is an interactive desktop tool for easy access, manipulation, and visualization of earth science data; the openGrADS project intends to develop advanced interfaces and extensions for GrADS. They emphasize ease of use on desktop computers and do not directly address the pressing issue of handling massive amounts of climate data.

Statistical Tool for Extreme Climate Analysis (STECA) provides a graphical user interface for users to compute statistics of daily atmospheric climate analysis, such as heat index, relative humidity, wind chill, etc. The GUI allows users to specify data files and select statistical functions. The extReams toolkit generates daily and seasonal statistics of weather. In contrast to both these tools, TECA detects extreme climate events in large climate datasets by exploiting parallelism on supercomputing platforms.

The NCAR Command Language [26] and NetCDF Operators [27] are powerful, general utilities for performing a range of operations (examining, subsetting, averaging, plotting) on climate data. Efforts such as ParCAL [7] and Pagoda [8] are developing parallel analogues of these utilities, enabling parallel processing on large datasets. Our effort is fairly specialized in this regard, we are developing a framework for parallel feature tracking and analysis.

Kendall, et al. [28] present the DStep system which is similar in spirit to our work. Their system allows for simplified traversal of spatio-temporal domains across a large scale distributed memory system. They use a MapReduce like framework to process data and merge the results. They also use sophisticated data management and parallel I/O techniques, and demonstrate teleconnection analysis on an ensemble dataset.

Finally, we note that a few visualization and analysis tools have been demonstrated to scale on large supercomputing platforms and process massive datasets. VisIt [29] and Paraview [30] belong to this category. However, these tools are designed to be general purpose, and are not specifically targeted for the climate community. It is possible to implement the features in TECA within the VTK pipelines of VisIt and Paraview, and expose some climate-specific features to users. We will explore this route in the future as a vehicle for production deployment to a broad user community.

5. Discussion and Future Work

Using TECA greatly simplifies the parallel implementation of the tropical storm, extra-tropical cyclone and atmospheric river detection analyses described in the previous section. TECA handles many of the common tasks involved with parallelizing the analysis, in particular: i) splitting of analysis tasks into independent subtasks, ii) execution of the subtasks in parallel, iii) collecting data from all MPI ranks and sorting of the collected data by using TECA's parallel table data structure for storage and exchange of analysis results, and iv) integration of different analysis task (e.g,. detection of storms and computation of storm trajectories) into a single analysis application. The object-oriented design of TECA provides developers with flexibility and and ease of integration of new features, such as new schemes for decomposition of analysis into subtasks, without having to modify TECA itself.

The current implementation of TECA achieves a number of the goals we had proposed, such as ease of use and native support for temporal parallelism; but it also has various limitations. While a developer may easily add new types of tasks and task-decompositions, TECA currently does not provide native support for spatial parallelism, i.e., TECA currently does not implement subtasks based on spatial sub-regions of the globe. This will likely be a limitation when data from kilometer scale atmospheric models becomes available. Simple forms of temporal parallelism, namely assigning one timestep per core, will introduce load balancing problems, wherein only a small subset of the cores will undertake a detailed search for sparse extreme events. This problem can be alleviated by assigning interleaved timesteps (or spatial subsets) across cores, or a more elaborate workload-driven dynamic load balancing scheme. Finally, TECA has little I/O support at the moment. TECA currently only provides a straightforward interface to climate data, while I/O operations are largely performed by the analysis algorithms. We plan to address these limitations in future work.

Our current performance numbers reflect tests at a single problem configuration: $\approx O(6000)$-way concurrency and primarily utilizing temporal parallelism. We would like to perform more extensive scalability tests by utilizing spatial, temporal and spatio-temporal parallelism across a variable number of cores. Mixing different parallel modalities will enable us to run at much larger concurrencies and will likely expose scalability bottlenecks.

6. Conclusion

In conclusion, we have presented a design for TECA that leverages different flavors of data parallelism currently available in large climate datasets. We have demonstrated the power of the toolkit by application to three important climate science problems, namely that of detecting tropical cyclones, extra-tropical cyclones and atmospheric rivers. We have tested these implementations on large TB sized climate datasets and demonstrated good runtime performance on thousands of cores. The TECA toolkit provides for an extensible framework that can be leveraged for implementing different feature detection and tracking algorithms for tackling large scale climate science problems.

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