Addressing Data Resiliency for Staging Based Scientific Workflows

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ABSTRACT

As applications move towards extreme scales, data-related challenges are becoming significant concerns, and in-situ workflows based on data staging and in-situ/in-transit data processing have been proposed to address these challenges. Increasing scale is also expected to result in an increase in the rate of silent data corruption errors, which will impact both the correctness and performance of applications. Furthermore, this impact is amplified in the case of in-situ workflows due to the dataflow between the component applications of the workflow. While existing research has explored silent error detection at the application level, silent error detection for workflows remains an open challenge. This paper addresses silent error detection for extreme scale in-situ workflows. The presented approach leverages idle computation resource in data staging to enable timely detection and recovery from silent data corruption, effectively reducing the propagation of corrupted data and end-to-end workflow execution time in the presence of silent errors. As an illustration of this approach, we use a spatial outlier detection approach in staging to detect errors introduced in data transfer and storage. We also provide a CPU-GPU hybrid staging framework for error detection in order to achieve faster error identification. We have implemented our approach within the DataSpaces staging service, and evaluated it using both synthetic and real workflows on a Cray XK7 system (Titan) at different scales. We demonstrate that, in the presence of silent errors, enabling error detection on staged data alongside a checkpoint/restart scheme improves the total in-situ workflow execution time by up to 22% in comparison with using checkpoint/restart alone.

KEYWORDS

Fault Tolerances, Silent Data Corruption, Error Detection, In-situ Workflows, Data Staging

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Figure 1: A typical data staging workflow.

1 INTRODUCTION

Scientific workflows running on emerging extreme-scale systems can provide new insights into some of the most important problems in science and society, such as those being addressed by the US Exascale Computing Program (ECP) [26]. However, extreme scales also lead to new challenges in areas such as data management, resilience, and energy efficiency. Research and innovation to address these challenges is ongoing at all levels, from hardware architectures and system software to algorithms and applications.

In-situ workflow approaches, such as those based on data staging and in-situ/in-transit data-management, have emerged as effective solutions for addressing data-related challenges at extreme scales, and are being adopted by applications across current high-end computing systems [11, 21]. The data staging area, i.e., a set of additional compute nodes allocated by the user when launching an application workflow, leverages resources (i.e., compute and memory) on the HPC system itself to support the interaction and data couplings required by the workflows as well as to execute data-processing components of the workflow close to where the data is being produced. This reduces the amount of data that needs to be moved off the system, for example to persistent storage [4]. One example of this is the coupled multi-scale, multi-physics turbulent combustion application S3D [9]. S3D has an intricate data-processing workflow that includes multiple analyses performed at different temporal frequencies on non-overlapping subsets of data, and staging-based in-situ frameworks such as DataSpaces [13] have been used effectively to support such workflows. Figure 1 illustrates a coupled simulation workflow, wherein the primary scientific simulation is the data producer and the data consumer(s) include secondary simulations, analytics services, and/or visualization applications coupled to the producer.

Recent research has also addressed resilience at extreme scales and the expected higher rates of fail-stop failures and silent errors (also called silent data corruption) [8]. These works have explored techniques for minimizing application vulnerability to such failures. However, the impact and remediation of such failures and errors on in-situ workflows has only recently been explored. The impact of failures and errors can potentially be amplified in the

case in-situ workflows due to the dependencies, interactions and data exchanges between the components of the workflow. While our previous work [15] has tried to minimize the impact of fail-stop failures on staging-based in-situ workflows, the impact and remediation of silent errors specifically on such in-situ workflows has not been explored to the best of our knowledge.

A silent error is an unintentional change to a bit in memory. These undetected bit flips impact the correctness and performance of applications and workflows [8]. These types of error events are already present and impactful in high-end computing. For example, silent errors have been observed to occur approximately once per day on Jaguar, located at Oak Ridge National Laboratory (ORNL), which is a 18688-node supercomputer and each node is equipped with 16GB of DRAM supercomputer [18, 19]. More recently, a detailed analysis of DRAM and SRAM faults on Hopper, a 6000-node supercomputer located at Lawrence Berkeley National Laboratory (LBNL), indicates that Hopper encounters ~32 FITs (failures per billion hours of operation) per DRAM device [22]. As systems approach extreme scales, these error rates will grow to become unacceptably high, leading to an increase in silent data corruption rates. If we expect the per-component fault rates in an extreme scale system to be similar to those observed in current devices, the mean time between undetected memory errors for the system as a whole will be on the order of minutes. Hardware-level error detection approaches alone, such as error-correcting codes (ECCs), cannot cover all silent errors and additionally need to cooperate with system-level and application-level error detection approaches to achieve maximally reliable system design [16, 20].

Although various error-detection techniques for silent errors, such as ABFT [7] and time-series predictions [6], have been widely studied, these studies have generally been in the context of single applications rather than workflows, which are a composition of multiple interacting component applications. As extreme scale workflows are often long-running and the final result of the workflow depends upon intermediate results, a silent error or data corruption in any component can invalidate the entire execution of the workflow, with substantial impact. As a result, it is important to detect and isolate silent errors in a component application as early as possible and to contain the propagation of these errors between components.

To that end, this paper explores the detection and remediation of silent errors for staging-based in-situ workflows. In this research, we leverage the fact that such in-situ workflows utilize data staging frameworks [13][14] to exchange data, and use idle computational resources within the data staging area to provide uniform and efficient error detection. Note that the paper does not focus on a specific error detection approach nor propose a new approach, but rather focuses on how existing approaches can be effectively used to provide data resiliency for staging-based in-situ workflows. Specifically, we perform data validation as soon as the data is written to the staging area. If an error is identified in recently written data, the faulty application is instructed to roll back to the last known correct checkpoint and re-execute. In this way, the application waiting to consume the written data will only get access to the correct data, and error propagation from producer to consumer is eliminated. We use a spatial outlier detection method for data validation as an

illustrative example in this paper, and also explore how the performance impact of data verification can be reduced by leveraging GPU resources at the staging nodes to execute the error detection algorithms.

We have implemented our staging based error-detection framework for in-situ workflows within DataSpaces [13] and have deployed it on the Titan Cray XK7 production system at Oak Ridge National Laboratory (ORNL). We then have evaluated its effectiveness and performance using both synthetic workloads and the S3D combustion workflow. These evaluations demonstrate that enabling error detection in the staging area can efficiently detect silent errors for various use cases, sustaining performance and scalability in spite of frequent silent errors.

The rest of the paper is organized as follows. In Section 2, we discuss background and motivation related to staging-based silent error detection for in-situ workflows as well as error detection approaches, and introduce our staging-based error detection framework in Section 3. In Section 4, we evaluate our approach using various synthetic and real-world scientific simulation workflows. Section 5 provides details of various related work, and the paper is concluded in Section 6.

2 BACKGROUND AND MOTIVATION

Each silent error is a potential threat to the data integrity of an HPC application. Silent errors may occur in the form of transient bit-flips and are typically caused by electronic noise or strikes by high energy particles, such as cosmic rays or proton radiation. Although the mean time between silent errors (which we will denote as MTBE in this paper) of individual components is high, at extreme scales the aggregate MTBE of the entire system is low due to the large number of system components. Additionally, silent errors are becoming more prevalent in HPC systems as lower power chips with smaller feature sizes are being deployed. Research has shown that there exists a strong inverse correlation between the spontaneous error rate and the device sizes and operating voltages [17]. Compounding the issue, scientific workflows, due to their complexity and long execution times, tend to encounter interruptions or obtain invalid results caused by silent errors at a relatively high rate. Therefore, data resiliency is a critical concern for scientific workflows running on extreme scale systems and efficient detection of silent errors is important for guaranteeing data resilience.

To this end, we make no assumptions about the source of the errors and they can come either from the hardware (error that are not correctable by ECC) or from the software due to incorrect programming logic. This paper focuses on silent errors that corrupt one or multiple bits of a floating-point scientific dataset silently, regardless of their origin, during the execution of the workflow.

2.1 Motivating Application Workflow

Extreme scale in-situ scientific workflows involve interactions and data exchanges between the various components composing the workflow. For example, consider the coupled combustion simulation DNS-LES workflow. S3D [9] is a massively parallel computational fluid dynamics (CFD) solver that performs first principles based "direct numerical simulations" (DNS) of turbulent combustion. DNS is very expensive both in terms of flops and data generation, since

Figure 2: Coupling and data-exchange patterns for the in-situ S3D coupled simulation workflow.

it resolves the entire range of spatial and temporal scales in the continuum regime of a given problem. Large Eddy Simulation (LES) simulates a combustion environments at a lower resolution, resulting in better performance for simulating features that can tolerate this lower resolution. Many problem classes involve features that cannot be performantly and accurately simulated by DNS or LES alone, but can be effectively simulated by a coupled solution, requiring in-situ coupling of two different solvers running at different resolutions. Furthermore, knowledge discovery and visualization from a S3D simulation run can be a daunting task due to the size of the data set generated and the complexity of the temporally evolving intermittent phenomena. To understand the correlation of scalar fields such as temperature, mixing rates and species concentrations in turbulent flames, simulation-time feature extraction and visualization is necessary.

The S3D workflow consists of S3D simulation and visualization coupling application, as illustrated in Figure 2. In each coupling cycle, the workflow first executes S3D simulation for several time steps, moves the data generated to the staging area, which is the processed by the analytics/visualization applications for feature extraction.

When the workflow passes data between the S3D simulation components and the visualization components, dozens of 3D scalar and vector field components (fluid velocity, molecular species concentrations, temperature, pressure, density, etc) are transferred using staging or other mechanisms. If there are silent errors in this data, these errors will also be propagated to the coupled components of the workflow. This will result in erroneous results in the visualization and analysis products. Even worse, in the case of multiphysics coupling, even small errors can have catastrophic results, especially to the stability of non-linear PDEs. These errors have the potential to significantly alter the accuracy of the simulation, and may not be otherwise detected by the simulation without expensive analysis on the invariant terms of the simulation.

To prevent such silent errors from propagating across components, we must identify and recover from data corruption before the data transfer is completed. While error detection algorithms can be hard-coded into applications and invoked before every data exchange, this can become quite expensive. In the case of staging-based in-situ workflows, data transfers between workflow components is done through staging, which provides an opportunity to leverage computational capabilities on the staging resources to perform error detection only on the exchanged data in an asynchronous manner. In this paper, we explore the feasibility add effectiveness of such an approach.

A further motivation for staging-based error detection is that simulation and analysis applications in workflows are commonly

Figure 3: Cumulative data write throughput (blue dot line) and CPU Utilization = compute time in staging/ write response time (red line) for different problem sizes when writing the entire data domain to data staging.

CPU-bound, so frequently performing error detection in such applications will significantly degrade the overall performance of the workflow. In contrast, we observed that staging resources tend to be relatively less heavily loaded compared to the computations nodes that run the workflow components. The indexing and data-transformation tasks associated with providing a data staging service are not generally CPU-intensive. Given this resource-usage pattern, it is reasonable to offload error detection task to data staging, which enables efficient error detection without suffering performance degradation. To demonstrate this, we performed experiments using a synthetic workflow on the Titan Cray XK7 system. The data used in this workflow is based on the S3D access patterns shown in Figure 2. 64 synthetic simulation processes wrote a set of n-dimensional arrays to 4 staging servers with varying staged data sizes in each time step. The arrays consist of uniform double-precision floating point data.

The amount written to each staging server per time step varied between 8M and 64M and total data size stored in the staging area through the life of the workflow varied between 320M and 2560M. Using this configuration, we measured the average write throughput and CPU utilization for the data staging servers under different workloads. The results are plotted in Figure 3. As the size of the workload was increased, the CPU utilization of the staging cores remained consistently low, while the write throughput has already reached the peak and decreased. In this particular test, the maximum CPU utilization was observed around 22% when the write size was 8M for each staging server per time step. This experiment illustrates that the compute resource in the staging area is not fully utilized and the staging performance is constrained by other resources limitation such as network congestion. Therefore, we have an opportunity to leverage compute resource within staging-area to perform error detection without degrading the read and write throughput of the staging service.

2.2 Silent Error Detection Techniques

Theoretically, any error detection approach at the software level is fit for a staging-based error detection framework. In this section, we will briefly talk about integrating three widely-used error detection approaches in data staging and figure out generality, accuracy and performance of each approach. The accuracy of error detection is

quantified by using two measures: *recall* and *precision*, which are defined as:

$$\text{recall} = \frac{\text{TruePositives}}{\text{TruePositives} + \text{FalseNegatives}}$$

$$\text{precision} = \frac{\text{TruePositives}}{\text{TruePositives} + \text{FalsePositives}}$$

2.2.1 Process Replication. Process replication [18] has been widely used for tolerating both silent errors and fail-stop failures. It creates replica tasks, such as MPI process, for each primary task and compares the computation results between replicated processes to detect corrupted data. This approach is very general, has high *recall* and *precision*. Unfortunately, process replication may not always be feasible because computing redundant tasks in the staging area will impose large overheads and significantly degrade throughput of the data request, since the compute resources in data staging are much smaller than that in application components.

2.2.2 Algorithm-Based Fault Tolerance. The general idea of Algorithm-Based Fault Tolerance (ABFT)[7] is to introduce information redundancy in the data, and maintain this redundancy during computation. Linear algebra operations over matrices are well-suited to apply such a scheme: the matrix (original data of the user) can be extended by a number of columns, in which checksums over the rows are stored for future data verification. It imposes a low overhead on the computation and guarantees good *recall* in general. The disadvantage of integrating ABFT in data staging is that this technique has only been implemented for a limited set of linear algebra application, and so is only available to a small subset of the vast spectrum of scientific applications.

2.2.3 Outlier Based Error Detection. Most of the datasets produced by HPC scientific applications have expected informational characteristics that reflect the properties of the underlining physical phenomena that the applications seek to model [20]. Silent data corruption via bit flips alters the value of the data causing it to deviate from these standard characteristics. Therefore, corrupted data can be detected as an outlier based on its deviation from the expected range of normal values. There are two classes of outlier detection: time-series outlier detection and spatial outlier detection. Time-series outlier detection [6] is illustrated in Figure 4(a). HPC scientific application often iteratively operate upon data, changing their values over time. At each iterative time-step, a time-series outlier detection approach can be used to dynamically predict the possible range for data values at the next time-step, and a data value can be considered as an outlier if it falls outside this range.

Spatial outlier detection [3] is illustrated in Figure 4(b). A spatial outlier is a spatially-referenced object whose non-spatial attribute

Figure 4: Examples of time series and spatial outlier detection techniques for a 1D data domain.

values are significantly different from those of other spatially referenced objects in its spatial neighborhood. A spatial neighborhood may be defined based on spatial attributes, e.g., location, using spatial relationships such as distance or adjacency. Non-spatial attributes between spatially referenced objects can be compared within that neighborhood, considering those values whose non-spatial attributes deviate significantly to be spatial outliers. Although not perfectly accurate, outlier detection techniques can still detect a substantial fraction of silent errors, and more importantly these methods incur low overhead. These properties make them attractive candidates for staging-based error detection.

Although outlier-based error detection approaches are good candidates for SDC-detection, it should be noted that the choice of the most appropriate error-detection approach depends on the data characteristics of the workflow; our work aims to provide a pluggable approach for enabling error-detection in the staging area and to highlight its benefits, and can use the chosen most appropriate error-detection approach for a specific workflow.

3 ERROR DETECTION IN STAGING

In this section, we first model our staging-based error detection framework. We then analyze it by simulating scientific workflow events and present factors that influence the rate of error detection in staging. Finally, we propose optimizations for implementing error detection approaches in the data-staging area and leveraging GPU resource (if available) to ameliorate the impact of performing error detection on common I/O operations.

3.1 Modeling Error Detection in Staging

Notations: Let C , T_c , and T_s denote the cost of checkpointing, the optimal time cycle for checkpointing, and the time cycle of error detection in staging, respectively. Let R_s represent the *recall* of error detection in staging, which is the proportion of detected errors over all errors that have occurred in the course of execution. If D is the cost of error detection in a given checkpoint component and D_s is the cost of error detection in staging, we assume that $D_s \ll D$, since the amount of data exchanged via staging area is much smaller than checkpoint data size. W_{base} denotes the base execution time of a workflow without any resilience technique. The notations that are used in the model are listed in Table 1.

Symbols	Explanation
C	Cost of checkpointing
T_c	Optimum time cycle for checkpoint
D	Error detection cost in the checkpointing component
T_s	Time cycle for error detection in data staging
D_s	Error detection cost in data staging
T_r	Time interval from last checkpoint to the error detection in data staging
R_s	<i>recall</i> of error detection in data staging
P_s	<i>precision</i> of error detection in data staging
P_f	Probability of silent errors during execution time
T_w	Time cycle for workflows pattern
W_{base}	Workflow execution time without resilience techniques and failures

Table 1: Symbols summary

Figure 5: An illustration of a typical workflow with two coupled simulations *simu1*, *simu2*. Simulations alternate in exchanging data via data staging. For fault tolerance, each simulation performs checkpointing and silent error detection tasks based on their optimal checkpoint time cycles.

Fault tolerance model: Scientific workflows typically employ a checkpoint/restart mechanism to periodically perform checkpointing tasks to enable rollback to the previous state in case of a fail-stop failure. To deal with both fail-stop failures and silent errors, checkpointing tasks are coupled with error detection (or verification) mechanisms. To guarantee that checkpoint data is error-free, error detection is performed just before checkpointing tasks [5]. If the verification fails, it can be assumed that a silent error has occurred and the application must rollback to the previous checkpoint for error-free data.

Figure 5 shows a typical workflow with a checkpointing scheme combined with error detection. In each checkpoint cycle, coupled simulations *simu1*, *simu2* can access staging servers and fetch or write data from/to the servers. Since data is stored in the staging area, we can improve the fault tolerance scheme by leveraging idle compute resource in the staging area to perform data verification. In this way, during each checkpoint cycle, there will be multiple error detections in the staging for early detection of silent errors and to save re-execution time. For the checkpointing scheme, a workflow makes a global checkpoint and performs error detection based on its optimal checkpoint time cycle for fail-stop failures. In the following analysis, we compare the approach where error detection occurs only at checkpoint-time with the approach that performs error detection in both staging and at the checkpoint. The goal of performing error detection in staging is to minimize the expected execution time of the workflow, $E(W)$.

3.1.1 Error detection in checkpoint component. Suppose that the probability of a silent error happening in the workflows is P_f . Let T_{DC} be the maximum cost for error detection and checkpoint of *simu1*, *simu2*: $\text{Max}(D_1 + C_1, D_2 + C_2)$. Let T_{cC} denote the maximum time chunk for two consecutive checkpoints: $\text{Max}(T_{c1} - C_1, T_{c2} - C_2)$. Also, error detection in the checkpoint component can always fully verify data. Then, the expected execution time of the workflow ($E(W_c)$) can be computed as:

$$E(W_c) = \frac{T_w}{T_c} (T_{DC} + P_f \times T_{cC}) + W_{base} \quad (1)$$

3.1.2 Error detection in checkpoint and staging. We now add an extra error detection in the staging area. Firstly, let us suppose that any silent error happening during T_s can be detected. That means *recall* and *precision* for error detection in staging are $R_s = 100\%$, $P_s = 100\%$. In this scenario, the workflow executes for an

extra D_s time until error detection in staging completes and sends an error notification back. Then, the workflow needs to rollback to the previous error-free checkpoint and discard $T_r + D_s$ time worth of work. Therefore, the expected execution time of the workflow ($E(W_s)$) can be computed as:

$$E(W_s) = \frac{T_w}{T_c} (T_{DC} + P_f(T_r + D_s)) + W_{base} \quad (2)$$

Then, we can make our model more realistic by only assuming that the *precision* of error detection in staging $P_s = 100$. In this case, the staging can detect R_s percent of silent errors and the remaining $1 - R_s$ percentage will be detected by the checkpoint component. Thus, the expected execution time of the workflow ($E(W_s)$) can be updated to:

$$\frac{T_w}{T_c} (T_{DC} + P_f((1 - R_s)T_{cC} + R_s(T_r + D_s))) + W_{base}$$

When the *recall* rate is R_s and the *precision* is P_s for the error detection in staging, the staging will generate $1 - P_s$ percentage needless rollback operations due to the introduction of false positives in detection. The penalty for false positives is $T_p = (1 - P_s)(T_r + D_s)$. Thus, the expected execution time of the workflow ($E(W_s)$) can be updated to:

$$\frac{T_w}{T_c} (T_{DC} + P_f((1 - R_s)T_{cC} + R_s(T_r + D_s) + T_p)) + W_{base}$$

From the above equations, it can be expected that adding error detection in the staging area can reduce the total workflow execution time in the presence of errors, which can be computed as:

$$E(W_c) - E(W_s) = \frac{T_w}{T_c} P_f (R_s(T_{cC} - T_r - D_s) - T_p) \quad (3)$$

3.2 Simulation and Analysis

In order to determine the expected advantage of this approach in practice, we simulate the execution of a scientific workflow using the parameters (i.e., $MTBF$, C , and T_c) suggested in [5], which are also listed in Table 2. For $MTBF$ and $MTBE$, we calculate the $MTBF$ and $MTBE$ of one computing node, which is 4.3 years for fail-stop failures and 7.9 years for silent errors. The overall $MTBF$ and $MTBE$ are obtained by dividing the per-node $MTBF$ and $MTBE$ by the total number of nodes running the workflow. For example, when 65536 nodes are used in extreme scale systems, the overall $MTBF$ and $MTBE$ are 2064s for fail-stop failures and 3784s for silent errors. The silent errors are generated by following an exponential distribution of parameter $\lambda = \frac{1}{MTBE}$. The disk checkpoint cost C is close to 300s, which is typical of many state-of-the-art platforms, such as Hera [5]. Under the assumed $MTBF$ for fail-stop failures and the checkpoint cost C , we get the optimum checkpoint cycle of 1491s through Daly's formula [25]. Furthermore, we assume that there is no relation between $MTBF$ and $MTBE$, and $MTBF$ will be kept constant in the simulation test cases. For error detection, we assume that the error detection in a checkpoint has a cost of 100s with the *recall* and *precision* of 100% and that error detection in staging has a cost of 4s with a *recall* 70% due to error detection being performed on a subset of the global data domain. We assume that the computation and communication cost of the workflow is 81920s (22.6hr), which does not include checkpointing and error detection tasks.

Figure 6: The simulated total work flow execution time comparison between error detection in checkpoint component (blue dot line) and error detection in both checkpoint and staging (solid line).

No. of case	Case 1	Case 2	Case 3	Case 4
<i>MTBE</i>	/	3784s	3784s	3784s
<i>C</i>	300s	300s	300s	300s
<i>D</i>	100s	100s	100s	100s
<i>T_c</i>	1491s	1491s	1491s	1491s
<i>P_s</i>	100%	/	100%	100%
<i>R_s</i>	70%	/	70%	70%
<i>D_s</i>	4s	4s	/	4s
<i>T_s</i>	600s	600s	600s	/
<i>T_w</i>	81920s	81920s	81920s	81920s

Table 2: The parameter configuration for workflow time sequence emulation.

Table 2 describes the inputs of the emulation program. The emulation results are presented in Figure 6, followed by a detailed discussion and analysis of each. The reported results are the average of 100 experimental runs.

In simulation case 1, where we vary the workflow’s *MTBE*, our approach has better performance than performing error detection only in checkpoint as long as *MTBE* is under 3784s. We performed analysis for different values of *recall* under *precision* = 100% and different values of *precision* under *recall* = 100% in simulation case 2. It can be seen that when *recall* is greater than 70% or *precision* is greater than 89%, error detection should be performed in the staging area. For the cost of error detection when it is less than 4s, error detection in staging outperforms the detection in checkpointing, which is illustrated in simulation case 3. To analyze the impact of *T_s*, we also varied *T_s* in simulation case 4 and observed that when *T_s* < 800s, our approach is beneficial and it maintains similar performance for higher values.

Based on Equation 3 and the analysis above, we can deduce that the advantage of enabling error detection in the staging depends on the following factors: (i) The frequency of silent errors *MTBE* (higher will see more advantage from the in-staging approach); (ii) The *recall* and *precision* of error detection in staging *R_s*, *P_s* (higher is better); (iii) The cost of error detection in staging *D_s* (lower is better); (iv) The frequency of staging operation *T_s* (performance will improve with less frequent staging operations).

In addition, unlike *recall*, lower *precision* can significantly deteriorate the performance of error detection in staging. Part of the reason for this is that lower *precision* indicates high false positive, which can unnecessarily rollback the workflow frequently. In contrast, lower *recall* corresponds to high false negative, which means

that CPU cycles are wasted performing error detection that is unable to detect silent errors. Generally, the cost of error detection in staging is much less than the cost of re-executing the workflow.

3.3 Implementing Error Detection in Staging

While the integration of error detection within a data staging framework seems straight-forward, naïve application of error detection technique in the data staging can result in significant performance degradation and low error detection accuracy. One of the challenges for error detection in staging is that the data staging framework stores data temporarily during data exchanges, so an entire spatial dataset is not always available. Another challenge for error detection in staging is that data staging has relatively limited compute resource, so an error detection approach having a long computation time could significantly degrade the performance of staging servers. Thus, an ideal error detection approach should maintain high accuracy, especially high *precision*, in error detection. Also, the approach should have light overhead and minimal impact on common data staging operations, such as *data put()* and *get()*.

In the following section, we introduce two optimization techniques which can achieve the twin goals of lightweight execution and high accuracy. We use Spatial Local Outlier Measure (SLOM) [24] as an example to illustrate how to integrate an error detection approach in the data staging efficiently. SLOM is a type of spatial outlier detection approach that can capture both spatial auto-correlation (non-independence) and spatial heteroscedasticity (non-constant variance), which are common features of scientific spatial datasets. In SLOM, the effects of spatial auto-correlation are factored out by a measure $d(o)$. The variance of a neighborhood is captured by $\beta(o)$, which quantifies the oscillation and instability of an area around o .

$$SLOM(o) = d(o) * \beta(o)$$

3.3.1 CPU-GPU Hybrid Staging. In an extreme-scale workflow, staging servers need to process thousands of requests. Thus, any delay caused by error-detection will interfere with servicing other requests, amplifying the impact, and potentially causing a significant delay across the whole workflow. To minimize this impact, we propose offloading workload to GPUs, when available. GPUs are now widely used as general purpose devices in HPCs. They enable significant speed-ups in performance for scientific computation and analysis tasks. Since silent error detection approaches are computation intensive tasks, we can leverage these GPUs to achieve

significant acceleration of error detection. Specifically, CPU cores in the dedicated staging node can be used to serve communication and regular staging operations, such as indexing and data storage, while the data from local CPU memory is offloaded to GPUs and GPU kernel performs the spatial outlier detection.

There are two main challenges in processing large amounts of data on the local GPU device: relatively limited bandwidth and small memory size. We address these issues as follows. The data staging process first partitions the larger geometric dataset into several smaller tiles, such that each tile fits into the GPU global memory. Next, the tiles are stored in a queue, which is located in CPU memory and is ready to be offloaded to GPU global memory. While the GPU threads process the tile, the next tile in the queue is prefetched into GPU global memory to hide the data transfer latency. This CPU-GPU hybrid staging approach can also be leveraged by CPU-only application workflows, such as the S3D simulation workflow. The pseudo code of spatial outlier error detection in CPU-GPU hybrid staging is provided in Algorithm 1. This can be easily extended to other error detection methods.

3.3.2 Tuning precision and recall in Staging. Although *recall* and *precision* both play a very important role for error detection in staging, from section 3.2, we can deduce that compared with *recall*, a lower *precision* can significantly deteriorate the performance of error detection in staging. In addition, many outlier-based error detection approaches output a score quantifying the level of 'outlierness' of each data point, but this value does not provide a concise summary of the small number of data points that should be considered as silent errors. Specifically, in SLOM simply identifying the data point with the maximum SLOM value as a silent error will virtually always produce a false positive.

In the following, we introduce dataset/feedback training which can tune *precision* and *recall* for outlier based error detection approaches so as to minimize false positives with acceptable false negatives. During the dataset training, we inserted synthetic bit flip errors into the staged dataset and monitored the minimum value that can just cover all synthetic errors, then we mark it as

Algorithm 1 Error Detection Processing

Input: spatial data P , meta data Q
Output: outlier value O_{max} , error decision $flag$

```

1: procedure DSPACES_PUT( $P$ )
2:    $flag = 0$ 
3:    $Detector\_Kernel(Q, P)$ 
4:   if  $O_{max} > threshold$  then
5:      $flag = 1$ 
6:   end if
7:   insert  $P$  into staging
8:   update meta data  $Q$ 
9: end procedure
10: procedure DETECTOR_KERNEL( $Q, P$ )
11:   for each point  $p$  in  $P$  do
12:      $D = d(p)$ 
13:      $B = beta(p)$ 
14:      $O = D * B$ 
15:      $O_{max} = Max(O, O_{max})$ 
16:   end for
17: end procedure

```

Figure 7: An illustration of the behavior of and relation between dataset training and feedback training.

Figure 8: Implementation of error detection in CPU-GPU hybrid staging

the error detection *threshold*. For simplification, in our implementation the synthetic silent errors are uniformly distributed along the dataset and bit position. The *threshold* may be different for different simulation time steps, datasets, and staging servers.

During the feedback training, at the initialization of runtime, staging servers systematically calculate a SLOM value for each data point and keep track of the maximum observed SLOM value, as error detection threshold *threshold*. The staging servers then start to perform error detection for the available dataset. When the staging server finds one silent error candidate and the workflow is re-executed from the last checkpoint, it goes into feedback training mode. The staging server compares the new SLOM value with the previous one which was detected as an error. If the new SLOM value in that area is under the *threshold*, that means the staging server accurately identified the silent error. Otherwise, the previously detected silent error is a false positive and *threshold* is raised. Figure 7 illustrates that feedback training tunes the detection *threshold* towards the error data distribution and achieves higher *precision* of error detection. Similarly, dataset training pushes the detection *threshold* toward a normal data distribution and achieves higher *recall*.

4 EXPERIMENTAL EVALUATION

In this section, we evaluate staging based error detection framework, implemented as an extension of DataSpaces [13], an open-source data staging framework, and perform evaluations using both real and synthetic applications in the presence of silent errors.

In Section 3, we described our model for error detection in staging. In this section, we provide a specific implementation for the model on Titan HPC system. Figure 8 shows the overall system

Total number of cores	(16 to 128) + 16 + 16 = 48 to 160
No. of writer cores	$2 \times 4 \times (2 \text{ to } 8) \times 4 \times 4 = 16 \text{ to } 128$
No. of staging cores/nodes	16/1
No. of reader cores	16
Volume size	$64 \times 128 \times 64 \text{ to } 256 \times 128 \times 128$
In-staging data size (20ts)	80 to 640 MB
Workflow pattern	Write immediately followed by Read
Cycle for error detection	1 time step

Table 3: Experimental setup for performance tests.

configuration for error detection in the workflow. In the Titan Cray XK7 system, each compute node contains a 16-core 2.2GHz AMD processor with 32 GB of DDR RAM, a NVIDIA Kepler accelerator (GPU) with 6 GB of GDDR RAM and a Cray Gemini high-speed interconnect. Although subsequent experiments are only run on Titan, recently deployed machines such as Summit (a 4,608-node supercomputer at Oak Ridge National Laboratory (ORNL)) also have GPUs attached to each node and our approach can benefit from these GPUs. Please note that our implementation of SLOM using CPU-GPU is just an example of an error detection method. The goal of the paper is to leverage idle staging resources to perform error detection using the error detection method of choice for staging based in-situ scientific workflows. The system architecture permits a key component: dedicated staging nodes, distinct from the application nodes. Simulation and analysis applications' processes run on application nodes. Before an application process checkpoints its entire data into the parallel file system, the process also performs an error detection locally to ensure data correctness. The DataSpaces coordination layer in application nodes sends dataset to staging servers through the DART layer (DataSpaces' data communication layer). After a staging server stores the data in local memory, it performs error detection in the staging nodes. For CPU-GPU hybrid staging, it will offload error detection into local GPU if the GPU compute resource is available for the dedicated staging node. When a silent error is detected, the staging server sends error message to application's checkpoint/restart components and triggers a process restart. In order to do that, we update the DataSpaces interface function *ds_put()* so that it can return the detection result back to applications and indicate if there is a silent error in the dataset.

We performed experiments that fall into four broad categories: performance experiments, synthetic test cases, and real-world large scale experiments. All staging servers run on dedicated compute nodes with GPU accelerators.

4.1 Performance Experiments

In this subsection, we evaluate whether applying idle resources in data staging to perform silent error detection has any adverse affect upon the applications connected to the staging servers. In order to quantify the interference (if any) caused by the proposed technique, we measure the write performance of the staging servers with error detection enabled. We also record write-response time without error detection in staging as a baseline. The setup of these experiments is described in Table 3.

Figure 9 shows the cumulative write-response time for staging servers with error detection. We can see that error detection involve much lower performance penalties even at large dataset in data staging. For example, for CPU-based error detection in staging,

Figure 9: Comparison of the data write-response time for data staging with error detection on Titan. *DataSpaces*: Data staging write response time without error detection (baseline); *DS_SLOM_C*: Data staging write response time with error detection in CPU staging; *DS_SLOM_G1024/8192*: Data staging write response time with error detection in CPU-GPU hybrid staging under 1024/8192 GPU threads.

Figure 10: Comparison of the total execution time of the workflow under different error detection frequencies or length of each time step in data staging. Error detection is performed in each time step.

the write response time overhead was no worse than 24.11% as compared to the same application without error detection. When we perform error detection in CPU-GPU hybrid staging, we see much lower overhead than the CPU-alone case. The write-response time increases by only 8.41% for the 1024 GPU thread case and 2.43% in the worst case for the 8192 GPU thread case as compared to the case of no error detection. Our approach shows good overall scalability and has minimal overhead as compared to the baseline.

We also explore the overhead of error detection in staging over different workflow configurations. We plot the total execution time for a workflow with different error detection cycle in Figure 10. In this experiment, we perform error detection in staging in each time step and keep $MTBE = 5$ minutes and checkpoint cycle $T_c = 2.5$ minutes constant. We then vary the length of the time steps from 10 seconds down to 1.25 seconds. Figure 10 shows that, for larger than 5 second time steps, the benefit for error detection in staging becomes significant, with a decrease of up to 22.5% in the total execution time as compared to error detection in only the local component checkpoint. For the frequent error detection or smaller length of each time step (between 1.25 and 5 second), error detection in staging does not provide much benefit. At the extreme, for the 1.25 second time step case error detection can trigger an overhead of 11.7%.

4.2 Synthetic Test Cases

To better understand the performance of error detection in staging and its effectiveness, we also design synthetic cases and evaluate the total execution time of the workflow. Our synthetic experiments were performed on Titan. In these experiments, both synthetic simulation and analysis applications have their own local error detection and checkpoint component. For simplification we assume that the local error detection in checkpoint component has 100% *recall* and *precision*. We checkpoint every 10 iterations and before checkpointing dataset into the parallel file system, error detection is performed, guaranteeing that the checkpoint is error-free. Besides detecting silent errors in the local checkpoint component, the error detection is also performed through staging servers after the data is staged. We also assume that *precision* of error detection in data staging is 100%, and *recall* is linearly related with the proportion of staged data. Once a silent error is detected, the workflow is rolled back to the last checkpoint and re-executed. We ran the synthetic workflow under varying proportions of staged data to total data and different frequency of error detection in staging. Then, we measure the total execution time of the workflow. In these experiments, two significant soft errors were randomly introduced into the dataset within the 40 time steps, which corresponds to $MTBE = 5min$. We re-run our experiments for 50 times and report the total execution time as an average of these runs. The set-up of these experiments is described in Table 4. The experimental results are presented in Figure 11 followed by a detailed discussion and analysis of each.

1) **Case 1 - Write the entire data domain in each time step under different MTBE:** Similar to simulation case 1 in Section 3.2, we vary MTBE (occurrence of silent errors) between 5, 7, 10, and 20 minutes which corresponds to 100, 75, 50, and 25 silent errors respectively being introduced during a total of 50 runs. Since data staging can detect silent errors and roll back workflow early in each time, the method of performing error detection in staging can get a relatively better total execution time than the error detection in local checkpoint component under the high frequent MTBE. This improves the total execution time of the workflow by 18.1% for $MTBE = 5min$, 14.3% for $MTBE = 7min$, 11% for $MTBE = 10min$ and 10.1% for $MTBE = 20min$ respectively, as compared to error detection in local checkpoint component only under correspond MTBE value.

2) **Case 2 - Write a subset of the data domain and perform error detection in each time step:** This case is effectively a combination of simulation case 2 and 3 in Section 3.2. In this case and other subsequent cases, we inject a total of 100 errors during 50 runs of the experiment. Since different percentage of whole data-set is exchanged via staging framework, there is variance in the *recall* and overhead of error detection in data staging, which is based on proportion of subdomain size to the entire data domain. Thus, error detection in staging has an increase in detected errors when the amount of data in staging area increases. Our approach reduced the total execution by around 7.6% for 40%, 11.3% for 60% and 14.2% for 80% subset data, as compared to the error detection in local checkpoint component only.

3) **Case 3 - Write the entire data domain in multiple time steps and perform error detection in each time step:** This case differs from the previous case, where a certain percentage of entire data domain

Figure 11: Breakdown of the total execution time (in seconds) for the workflows with checkpoint restart and error detection under 2 silent errors. Execute: Time spent in workflow execution; **Checkpoint:** Time spent to perform checkpointing; **Restart:** Time spent to restart workflow; **Detect:** Time spent performing error detection in staging; **Re-execute:** Time spent for re-executing the workflow from last checkpoint (correct error). The leftmost bar represents error detection in local checkpoint component only. Other bars represent error detection in both staging and local checkpoint components. Numbers on top of the bars indicate the total number of errors that was corrected by the staging component during 50 experiment runs.

was written in a time step. In this case, although a subset in written in each step, data staging can stages entire data domain in between 2 to 3 time steps. This enables staging framework to have high cumulative *recall*. Therefore, error detection in staging reduces the total execution time (around 14.9% for 40%, 16.3% for 60% and 16.9% for 80% subset data) as compared to error detection in local checkpoint component only.

4) **Case 4 - Write the entire data domain and perform error detection with different time step cycle:** Like simulation case 4 in Section 3.2, the entire data domain is written into the data staging periodically for every 1, 2, 4, 8 time steps separately. For error detection in staging, as the entire data is staged, a high *recall* of error detection is achieved. We can thus detect silent errors in the staging area and roll back the workflow immediately. Therefore, error detection in staging achieves a decrease of 2.2% for 8ts, 8.4% for 4ts, 13.8% for 2ts and 18.1% for 1ts in the total execution time relative to error detection in the local checkpoint component only.

Total number of cores	$96 + 16 + 16 = 128$
No. of writer cores	$6 \times 4 \times 4 = 96$
No. of staging cores/nodes	16/1
No. of reader cores	16
Volume size	$192 \times 128 \times 128$
In-staging data size (40 ts)	960MB
Workflow pattern	Write immediately followed by read
Local checkpoint, detection cycle	10ts

Table 4: Experimental setup for synthetic test cases.

No. of cores	4416	8832	17664
No. of simulation cores	4096	8192	16384
No. of staging cores/nodes	256/16	512/32	1024/64
No. of analysis cores	64	128	256
Volume size	$256 \times 256 \times 256$	$512 \times 256 \times 256$	$512 \times 512 \times 256$
Data size (GB)	110	220	440
Checkpoint cycle	10ts	10ts	10ts
Detection cycle of staging	1ts	1ts	1ts
MTBE of silent error	300sec	300sec	300sec

Table 5: Configuration of core-allocations, data sizes, and data resilience for the three test scenarios on 4416, 8832 and 17664 cores.

4.3 Large Scale S3D Experiment

We perform large scale tests of our method using the combustion DNS-LES simulation/analysis from the S3D combustion and analysis workflow [9] on Titan and compare it with error detection-only in the local checkpoint component. We also integrate error detection algorithm within S3D before checkpointing. Our staging-based error detection framework is tested using three different core counts (4416, 8832 and 17664) and corresponding grid domain sizes so that each core is assigned a spatial sub-domain of size $16 \times 16 \times 16$. In each time steps, 60%, 80%, 100% percentage of entire data passes through data staging separately. The total execution time of the workflow over 40 time steps is measured. Other core configurations, and data resilience setup are detailed in Table 5.

Figure 12 and Figure 13 illustrate the experimental results for the total execution time of S3D coupled simulation and analysis application workflow for various scale in the presence of silent errors. We also measure the *precision* and *recall* of error detection in staging. For all tests, the *precision* always equals 100%, and the value of *recall* is shown on top of the bars in Figure 12 and Figure 13. For all error detection approaches, the workflow with error detection in CPU-GPU hybrid staging always shows lower execution time than the corresponding workflow running with CPU-based staging alone. Under error detection in CPU-only staging techniques with the presence of silent errors, error detection in staging reduces the total workflow execution time by up to 14.4%, 16.5%, and 18.9% as compared to error detection in only the local checkpoint component on 4416, 8832, and 17664 cores, respectively.

The same trend can also be seen in the CPU-GPU hybrid staging. The error detection in staging improves the total execution time by up to 14.1%, 22.6% and 15.4% as compared to a workflow with error detection in only the local checkpoint component. In addition, when error detection is performed in staging, it was observed that the greater the fraction of the dataset being put into staging and verified, the lower the total execution time in the presence of errors. These results demonstrate that error detection in staging achieves

Figure 12: Comparison of the total execution time (in seconds) for the S3D simulation and coupled analysis workflow with error detection in CPU staging. Numbers on top of the bars indicate the *recall* of error detection in staging.

good overall scalability with small overhead for different processor counts and data sizes on extreme scale HPC systems.

Another concern for error detection in data staging is about the extra energy consumption involved in utilizing a data staging area. For this paper, we did not explore energy optimization approaches for error detection in data staging, nor conduct experiments to evaluate energy consumption. Although evaluations of energy efficiency are beyond the scope of the paper, we can make some general statements about the energy consumption of our approach. Error detection in data staging introduces three main operations: data computation, data storage, and data movement. Transporting data across compute nodes and storing it in DRAM devices increase the energy consumption [12]. Although it seems that adding error detection will increase the energy consumption for the workflow, if we consider that error detection in staging can decrease the total workflow execution time by eliminating substantial computation time in the presence of silent errors, we expect the energy consumption of the workflow to decrease.

5 RELATED WORK

Considerable efforts have been directed at developing techniques to detect and remediate silent errors. Process replication or redundancy techniques [18] can achieve a high *recall* and *precision* of detection with commensurately high compute and storage cost. Algorithm-based fault tolerance (ABFT) [7] can be very useful in decreasing the error detection cost and are specifically fit for detecting errors in linear algebra kernels using checksums. Detectors based on data analytics have been explored recently to serve as lightweight error detection methods[6, 20]. These approaches use interpolation techniques, such as time series prediction and spatial multivariate interpolation on the scientific dataset. In contrast to these efforts, we provide a framework for in-situ workflows for performing error detection. In addition, any error detection techniques can be easily integrated with our staging based error framework.

Since fail-stop failure is another significant risk for applications and checkpoint/restart has become a standard technique to address it, some research has combined checkpoint/restart with error detection approaches in order to deal with both fail-stop failure and silent errors. The study in [5] provides optimal resilience patterns to cope with fail-stop and silent errors. The research in [10] introduces an on-line ABFT based error detection approach and uses

Figure 13: Comparison of the total execution time (in seconds) for the S3D simulation and coupled analysis workflow with error detection in CPU-GPU hybrid staging. Numbers on top of the bars indicate the recall of error detection in staging.

it in conjunction with checkpoint/restart to improve the time required to obtain correct results in an unreliable computing system. These approach are mainly designed for single applications and do not solve the problem of error propagation between coupled application. Our approach specifically targets the coupled scientific simulations and aims to eliminate error propagation via data verification in the shared abstraction, or staging area.

The use of a data staging area has been exploited in several research efforts such as DataStager [2], PreData [27], JITStaging [1], DataSpaces [13]/ActiveSpaces [14], and Stacker [23]. Most of these existing data staging solutions focus primarily on fast and asynchronous data movement between components in workflow to lessen the impact of expensive I/O operations. In contrast, we present a staging-based error detection framework to fully utilize idle computation capabilities of staging nodes and provide an uniform lightweight error detection service for in-situ workflows.

6 CONCLUSION AND FUTURE WORK

Cutting-edge in-situ workflows are generating and consuming data at an ever-growing scale. Silent data corruption is an important issue that needs to be addressed in order to allow these workflows to continue scaling efficiently. In this paper we have presented a staging-based framework for detecting corruption that uses idle computation resource to effectively detect silent errors for in-situ workflows. As an illustrative example, we have demonstrated the use of an improved spatial outlier detection technique to achieve lightweight error detection with high accuracy. We have also provided a CPU-GPU hybrid staging architecture to minimize the impact of error detection on regular I/O operations on a data staging framework.

We have implemented staging based error detection on top of the DataSpaces framework and deployed it on Titan. We have evaluated the effectiveness and performance of our method through accuracy tests, performance tests, synthetic tests and real world large scale S3D application runs. Our experiments demonstrate that staging based error detection framework can effectively reduce the total execution time of scientific workflows when combined with checkpoint/restart. While we evaluated our approach using synthetic tests and the S3D combustion workflow on Titan, as future work we plan to investigate the impact of our approach on other classes of application workflows and machines. We also plan to explore other error detection approaches in staging and evaluate

the cost/accuracy trade-offs of these approaches on application workflows.

7 ACKNOWLEDGMENTS

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Appendix: Artifact Description/Artifact Evaluation

SUMMARY OF THE EXPERIMENTS REPORTED

We evaluate the staging based error detection framework, implemented as an extension of DataSpaces. In experiments, all staging servers run on the dedicated compute nodes with GPU accelerator on CRAY XK-7.

(1) Performance experiments: run 5 times and calculate average/means as the result, and standard deviation as the error bar.

(2) Synthetic test cases: run 50 times and calculate average/means as the result, and standard deviation as the error bar.

(3) Real-world large scale experiments: run 3 times and calculate average/means as the result, and standard deviation as the error bar.

ARTIFACT AVAILABILITY

Software Artifact Availability: All author-created software artifacts are maintained in a public repository under an OSI-approved license.

Hardware Artifact Availability: There are no author-created hardware artifacts.

Data Artifact Availability: There are no author-created data artifacts.

Proprietary Artifacts: There are associated proprietary artifacts that are not created by the authors. Some author-created artifacts are proprietary.

List of URLs and/or DOIs where artifacts are available:

<https://github.com/shaohuaduan/datastaging-error-detection>

BASELINE EXPERIMENTAL SETUP, AND MODIFICATIONS MADE FOR THE PAPER

Relevant hardware details: Cray XK-7

Operating systems and versions: Cray Linux

Compilers and versions: pgc 18.4.0

Applications and versions: S3D 15Oct09, DataSpaces-1.6.1

Libraries and versions: ugni 6.0, cray-mpich 7.6.3

Paper Modifications: We implemented SLOM as an example of staging based error detection framework, integrated it with DataSpaces-1.6.1.

Output from scripts that gathers execution environment information.

```
CRAY_CUDAToolKIT_VERSION=9.1.85_3.10-1.0502.df1cc54.1
↳ 3.1
LESSKEY=/etc/lesskey.bin
MODULE_VERSION_STACK=3.2.10.6
KSH_AUTOLOAD=1
PE_LIBSCI_VOLATILE_PRGENV=CRAY GNU INTEL PGI
```

```
PE_SMA_DEFAULT_PKGCONFIG_VARIABLES=PE_SMA_COMPFLAG_@
↳ prgenv@
PE_TPSSL_64_DEFAULT_GENCOMPS_INTEL_mic_knl=160
MANPATH=/opt/nvidia/cudatoolkit9.1/9.1.85_3.10-1.050
↳ 2.df1cc54.3.1/doc/man:/opt/gcc/6.3.0/snos/share/
↳ man:/sw/xk60/environment-modules/3.2.10.3/sles11
↳ .3_gnu4.9.0/share/man:/sw/sources/hpss/man:/sw/x
↳ k6/man:/sw/xk6/hsi/5.0.2.p1/sles11.5/man:/autofs
↳ /nccs-svm1_sw/titan/.swci/0-login/opt/spack/2017
↳ 0612/linux-suse_linux11-x86_64/gcc-5.3.0/git-2.1
↳ 3.0-znpqlkovoclvt5rwm3rpkp7d2m56ez2/share/man:/
↳ sw/xk6/lustredu/1.4/sles11.3_gnu4.8.2/man:/opt/c
↳ ray/atp/2.1.1/man:/opt/cray/libsci/16.11.1/man:/
↳ opt/cray/man/csmlversion:/opt/pgi/18.4.0/linux86
↳ -64/18.4/man:/opt/cray/mpt/7.6.3/gni/man/mpich:/o
↳ pt/cray/craype/2.5.13/man:/opt/cray/llm/default/
↳ man:/opt/cray/lustre-cray_gem_s/2.8.2.3.0.101_0.
↳ 46.1_1.0502.8871-1.0502.0.44.1/man:/opt/cray/alp
↳ s/5.2.4-2.0502.9950.37.1.gem/man:/opt/modules/3.
↳ 2.10.6/share/man:/opt/moab/share/man:/usr/local/
↳ man:/usr/share/man:/usr/man:/opt/cray/share/man:
↳ /opt/cray/man
INFODIR=/usr/local/info:/usr/share/info:/usr/info
NNTPSERVER=news
PE_PAPI_DEFAULT_ACCEL_FAMILY_LIBS_nvidia=-lcupti,-l
↳ cudart,-lcuda
PE_PETSC_DEFAULT_GENCOMPILERS_CRAY_sandybridge=8.6
PE_PETSC_DEFAULT_GENCOMPS_CRAY_skylake=86
PE_TPSSL_DEFAULT_GENCOMPS_INTEL_x86_skylake=160
PE_CXX_PKGCONFIG_LIBS=mpichcxx
PE_MPICH_GENCOMPILERS_PGI=15.3
GNU_VERSION=6.3.0
PE_LIBSCI_DEFAULT_GENCOMPS_GNU_mic_knl=51
PE_HDF5_DEFAULT_REQUIRED_PRODUCTS=PE_MPICH
HOSTNAME=titan-batch3.ccs.ornl.gov
CRAY_UDREG_INCLUDE_OPTS=-I/opt/cray/udreg/2.3.2-1.05
↳ 02.10518.2.17.gem/include
PE_FFTW_DEFAULT_TARGET_mic_knl=mic_knl
PE_LIBSCI_ACC_DEFAULT_PKGCONFIG_VARIABLES=PE_LIBSCI_
↳ ACC_DEFAULT_NV_SUFFIX_@accelerator@
PE_PETSC_DEFAULT_GENCOMPILERS_INTEL_mic_knl=16.0
PE_PETSC_DEFAULT_GENCOMPS_PGI_x86_64=179
PE_TPSSL_64_DEFAULT_GENCOMPS_INTEL_interlagos=160
PE_TRILINOS_DEFAULT_GENCOMPS_CRAY_x86_64=86
SPACK_ROOT=/ccs/home/USER/codar/spack
PBS_VERSION=TORQUE-6.1.1.h2
XKEYSYMDB=/usr/share/X11/XkeysymDB
CRAY_SITE_LIST_DIR=/etc/opt/cray/modules
```

```

LIBRARYMODULES=acml:alps:cray-dwarf:cray-fftw:cray-g
↳ a:cray-hdf5:cray-hdf5-parallel:cray-libsci:cray-
↳ libsci_acc:cray-mpich:cray-mpich-abi:cray-mpich2
↳ :cray-netcdf:cray-netcdf-hdf5parallel:cray-paral
↳ lel-netcdf:cray-petsc:cray-petsc-complex:cray-sh
↳ mem:cray-tpsl:cray-trilinos:cuatoolkit:fftw:ga:
↳ hdf5:hdf5-parallel:iobuf:libfast:netcdf:netcdf-h
↳ df5parallel:ntk:onesided:papi:petsc:petsc-comple
↳ x:pmi:tpsl:trilinos:xt-libsci:xt-mpich2:xt-mpt:x
↳ t-papi
RCLOCAL_BASEOPTS=true
PE_ACML_DEFAULT_DIR_GNU=gfortran64
PE_NETCDF_DEFAULT_VOLATILE_PKGCONFIG_PATH=/opt/cray/
↳ netcdf/4.4.1.1.3/@PRGENV@/PE_NETCDF_DEFAULT_GEN
↳ COMPS@/lib/pkgconfig
PE_PARALLEL_NETCDF_DEFAULT_VOLATILE_PKGCONFIG_PATH=/
↳ opt/cray/parallel-netcdf/1.8.1.3/@PRGENV@/PE_PA
↳ RALLEL_NETCDF_DEFAULT_GENCOMPS@/lib/pkgconfig
PE_SMA_DEFAULT_COMPFLAG_GNU=-fcray-pointer
PE_TPSL_64_DEFAULT_GENCOMPS_PGI_x86_64=153
PE_TRILINOS_DEFAULT_VOLATILE_PKGCONFIG_PATH=/opt/cra
↳ y/trilinos/12.10.1.1/@PRGENV@/PE_TRILINOS_DEFAU
↳ LT_GENCOMPS@/PE_TRILINOS_DEFAULT_TARGET@/lib/pk
↳ gconfig
PE_ACML_DEFAULT_DIR_DEFAULT64=_int64
PE_ENV=PGI
PE_HDF5_DEFAULT_GENCOMPILERS_GNU=5.1 4.9
PE_MPICH_ALTERNATE_LIBS_dpm=_dpm
PE_SMA_DEFAULT_COMPFLAG=
PE_TPSL_64_DEFAULT_GENCOMPILERS_CRAY_x86_64=8.6
PBS_ACCOUNT=CSC143
SHELL=/bin/bash
HOST=titan-batch3
PE_ACML_DEFAULT_TARGET_interlagos=_fma4
PE_TPSL_DEFAULT_GENCOMPS_CRAY_x86_skylake=86
PKGCONFIG_ENABLED=1
HISTSIZE=1000
PROFILEREAD=true
PE_PETSC_DEFAULT_GENCOMPS_CRAY_sandybridge=86
PE_TPSL_DEFAULT_GENCOMPILERS_GNU_x86_skylake=6.1
XTOS_VERSION=5.2.82
PBS_JOBNAME=test_dspaces_titan
CRAY_UGNI_POST_LINK_OPTS=-L/opt/cray/ugni/6.0-1.0502
↳ .10863.8.28.gem/lib64
CRAY_XPMEM_POST_LINK_OPTS=-L/opt/cray/xpmem/0.1-2.05
↳ 02.64982.7.26.gem/lib64
CRAYPE_DIR=/opt/cray/craype/2.5.13
PE_NETCDF_DEFAULT_VOLATILE_PRGENV=GNU
PE_PARALLEL_NETCDF_DEFAULT_VOLATILE_PRGENV=GNU
PE_PETSC_DEFAULT_GENCOMPS_GNU_haswell=53 49
PE_PETSC_DEFAULT_GENCOMPS_INTEL_haswell=160
PE_PETSC_DEFAULT_GENCOMPS_PGI_interlagos=179
PE_TPSL_64_DEFAULT_GENCOMPS_INTEL_x86_skylake=160
PE_TPSL_DEFAULT_GENCOMPS_GNU_sandybridge=51 49
PE_TPSL_DEFAULT_REQUIRED_PRODUCTS=PE_MPICH:PE_LIBSCI
PE_TRILINOS_DEFAULT_VOLATILE_PRGENV=CRAY GNU INTEL

```

```

PE_MPICH_DIR_PGI_DEFAULT64=64
OLCF_MODULATOR=/sw/sources/modulator/1.2.0
TMPDIR=/tmp/scratch
PERL5LIB=/opt/roab/lib/perl5
PE_ACML_DEFAULT_DIR_CRAY=gfortran64
PE_FFTW_DEFAULT_VOLATILE_PKGCONFIG_PATH=/opt/cray/ff
↳ tw/3.3.6.2/@PE_FFTW_DEFAULT_TARGET@/lib/pkgconfig
PE_HDF5_DEFAULT_VOLATILE_PRGENV=GNU
PE_HDF5_PARALLEL_DEFAULT_VOLATILE_PKGCONFIG_PATH=/op
↳ t/cray/hdf5-parallel/1.10.0.3/@PRGENV@/PE_HDF5_
↳ PARALLEL_DEFAULT_GENCOMPS@/lib/pkgconfig
PE_LIBSCI_DEFAULT_GENCOMPILERS_CRAY_mic_knl=8.5
PE_LIBSCI_GENCOMPS_CRAY_mic_knl=85
PE_NETCDF_HDF5PARALLEL_DEFAULT_VOLATILE_PKGCONFIG_PA
↳ TH=/opt/cray/netcdf-hdf5parallel/4.4.1.1.3/@PRGE
↳ NV@/PE_NETCDF_HDF5PARALLEL_DEFAULT_GENCOMPS@/li
↳ b/pkgconfig
PE_PETSC_DEFAULT_GENCOMPILERS_PGI_x86_64=17.9
PE_PETSC_DEFAULT_GENCOMPS_CRAY_interlagos=86
PE_TPSL_64_DEFAULT_GENCOMPILERS_PGI_interlagos=15.3
CRAY_MPICH2_DIR=/opt/cray/mpt/7.6.3/gni/mpich-pgi/15
↳ .3
ALT_LINKER=/sw/xk6/xalt/0.7.5/bin/ld
LIBRARY_PATH=/autofs/nccs-svm1_sw/titan/.swci/0-logi
↳ n/opt/spack/20170612/linux-suse_linux11-x86_64/g
↳ cc-5.3.0/git-2.13.0-znpqlkovoclvt5rwm3rkpk7d2m5
↳ 6ez2/lib
XALT_DIR=/sw/xk6/xalt/0.7.5
CRAY_CUDAToolKIT_POST_LINK_OPTS=-L/opt/nvidia/cudato
↳ olkit9.1/9.1.85_3.10-1.0502.df1cc54.3.1/lib64
↳ -L/opt/nvidia/cudatoolkit9.1/9.1.85_3.10-1.0502.
↳ df1cc54.3.1/extras/CUPTI/lib64 -Wl,--as-needed
↳ -Wl,-lcupti -Wl,-lcudart -Wl,--no-as-needed
↳ -L/opt/cray/nvidia/default/lib64 -lcuda
PE_GA_DEFAULT_VOLATILE_PRGENV=GNU
PE_LIBSCI_DEFAULT_GENCOMPS_GNU_x86_64=61 51 49
PE_TPSL_64_DEFAULT_GENCOMPILERS_CRAY_interlagos=8.6
PE_TPSL_DEFAULT_GENCOMPS_CRAY_mic_knl=86
CRAY_PRGENVPGI=loaded
PBS_ENVIRONMENT=PBS_BATCH
MORE=-s1
FPATH=/opt/modules/3.2.10.6/init/sh_funcs/no_redire
↳ ct:/opt/modules/3.2.10.6/init/sh_funcs/no_redire
↳ ct
PE_LIBSCI_ACC_DEFAULT_GENCOMPS_CRAY_x86_64=85
PE_LIBSCI_ACC_DEFAULT_REQUIRED_PRODUCTS=PE_MPICH:PE_
↳ LIBSCI
PE_LIBSCI_GENCOMPILERS_CRAY_mic_knl=8.5
PE_MPICH_DEFAULT_GENCOMPILERS_GNU=5.1 4.9
PE_PKGCONFIG_PRODUCTS=PE_LIBSCI:PE_MPICH
PE_TPSL_DEFAULT_GENCOMPS_INTEL_x86_64=160
PE_MPICH_GENCOMPS_GNU=51 49
QTDIR=/usr/lib/qt3
PE_PAPI_DEFAULT_ACCEL_LIBS_nvidia35=-lcupti,-lcudar
↳ t,-lcuda

```

Addressing Data Resiliency for Staging Based Scientific Workflows

```
PE_PETSC_DEFAULT_REQUIRED_PRODUCTS=PE_MPICH:PE_LIBSC
  ↳ I:PE_HDF5_PARALLEL:PE_TPSL
PE_TPSL_64_DEFAULT_GENCOMPS_CRAY_haswell=86
PE_TPSL_64_DEFAULT_VOLATILE_PKGCONFIG_PATH=/opt/cray
  ↳ /tpsl/17.11.1/@PRGENV@64/@PE_TPSL_64_DEFAULT_GEN
  ↳ COMPS@/@PE_TPSL_64_DEFAULT_TARGET@/lib/pkgconfig
PE_CRAY_DEFAULT_FIXED_PKGCONFIG_PATH=/opt/cray/paral
  ↳ lel-netcdf/1.8.1.3/CRAY/8.6/lib/pkgconfig:/opt/c
  ↳ ray/netcdf-hdf5parallel/4.4.1.1.3/CRAY/8.6/lib/p
  ↳ kgconfig:/opt/cray/netcdf/4.4.1.1.3/CRAY/8.6/lib
  ↳ /pkgconfig:/opt/cray/hdf5-parallel/1.10.0.3/CRAY
  ↳ /8.6/lib/pkgconfig:/opt/cray/hdf5/1.10.0.3/CRAY/
  ↳ 8.6/lib/pkgconfig:/opt/cray/ga/5.3.0.7/CRAY/8.4/
  ↳ lib/pkgconfig
PE_TRILINOS_DEFAULT_GENCOMPILERS_CRAY_x86_64=8.6
PBS_O_WORKDIR=/lustre/atlas2/csc143/scratch/USER/dua
  ↳ nspaper
PE_LIBSCI_DEFAULT_OMP_REQUIRES_openmp=_mp
PE_PETSC_DEFAULT_GENCOMPILERS_PGI_interlagos=17.9
PE_PETSC_DEFAULT_GENCOMPS_CRAY_x86_64=86
PE_TPSL_64_DEFAULT_GENCOMPILERS_CRAY_sandybridge=8.6
PE_TPSL_64_DEFAULT_GENCOMPILERS_PGI_x86_64=15.3
PE_FORTTRAN_PKGCONFIG_LIBS=mpichf90
PE_SMA_DEFAULT_VOLATILE_PKGCONFIG_PATH=/opt/cray/mpt
  ↳ /7.6.3/gni/sma@PE_SMA_DEFAULT_DIR_DEFAULT64@/lib
  ↳ 64/pkgconfig
ALLINEA_QUEUE_DLL=/opt/cray/mpt/7.6.3/gni/mpich-pgi/
  ↳ 15.3/lib/libtvmich.so.3.0.1
LC_ALL=POSIX
ALPS_APP_ID=20266923
PE_ACML_DEFAULT_DIR_INTEL=ifort64
PE_LIBSCI_ACC_DEFAULT_VOLATILE_PRGENV=CRAY GNU
PE_TRILINOS_DEFAULT_GENCOMPS_INTEL_x86_64=160
CRAY_MPICH_BASEDIR=/opt/cray/mpt/7.6.3/gni
USER=USER
PBS_TASKNUM=1
JRE_HOME=/usr/lib64/jvm/java/jre
PE_ACML_DEFAULT_TARGET_x86_64=
PE_HDF5_PARALLEL_DEFAULT_GENCOMPILERS_GNU=5.1 4.9
PE_NETCDF_HDF5PARALLEL_DEFAULT_GENCOMPILERS_GNU=5.1
  ↳ 4.9
PE_TPSL_64_DEFAULT_GENCOMPS_CRAY_x86_skylake=86
PE_TPSL_64_DEFAULT_GENCOMPS_INTEL_haswell=160
CRAYPE_LINK_TYPE=dynamic
LS_COLORS=
PE_FFTW_DEFAULT_TARGET_interlagos=interlagos
PE_LIBSCI_DEFAULT_VOLATILE_PRGENV=CRAY GNU INTEL PGI
PE_LIBSCI_GENCOMPILERS_GNU_mic_knl=5.1
PE_PETSC_DEFAULT_GENCOMPILERS_INTEL_interlagos=16.0
PE_TPSL_64_DEFAULT_GENCOMPILERS_INTEL_mic_knl=16.0
PE_TPSL_DEFAULT_GENCOMPS_CRAY_x86_64=86
PE_TRILINOS_DEFAULT_GENCOMPILERS_GNU_x86_64=5.1 4.9
PE_TRILINOS_DEFAULT_GENCOMPILERS_INTEL_x86_64=16.0
```

```
LD_LIBRARY_PATH=/opt/gcc/6.3.0/snos/lib64:/autofs/nc
  ↳ cs-svm1_sw/titan/.swci/0-login/opt/spack/2017061
  ↳ 2/linux-suse_linux11-x86_64/gcc-5.3.0/git-2.13.0
  ↳ -znpqlkovoc1vlt5rwm3rkpk7d2m56ez2/lib:/opt/pgi/18
  ↳ .4.0/linux86-64/18.4/lib
PBS_O_HOME=/ccs/home/USER
PE_LIBSCI_PKGCONFIG_VARIABLES=PE_LIBSCI_OMP_REQUIRES
  ↳ _@openmp@
PE_PETSC_DEFAULT_VOLATILE_PRGENV=CRAY CRAY64 GNU
  ↳ GNU64 INTEL INTEL64 PGI PGI64
PE_PKGCONFIG_LIBS=cray-cudatoolkit:AtpSigHandler:lib
  ↳ sci_mpi:libsci:mpich
PE_TPSL_64_DEFAULT_GENCOMPILERS_GNU_sandybridge=5.1
  ↳ 4.9
PE_TPSL_64_DEFAULT_GENCOMPILERS_INTEL_haswell=16.0
PE_MPICH_FIXED_PRGENV=INTEL
XNLSPATH=/usr/share/X11/nls
PE_PETSC_DEFAULT_GENCOMPILERS_CRAY_mic_knl=8.6
PE_PETSC_DEFAULT_GENCOMPILERS_CRAY_x86_64=8.6
PE_PETSC_DEFAULT_GENCOMPILERS_INTEL_skylake=16.0
PE_PETSC_DEFAULT_GENCOMPS_GNU_interlagos=53 49
PE_PETSC_DEFAULT_GENCOMPS_GNU_sandybridge=53 49
PE_PETSC_DEFAULT_GENCOMPS_INTEL_interlagos=160
PE_PETSC_DEFAULT_GENCOMPS_INTEL_sandybridge=160
PE_TPSL_DEFAULT_GENCOMPS_GNU_haswell=51 49
WORKDIR=/tmp/work/USER
ENV=/etc/bash.bashrc
MPICH_ABORT_ON_ERROR=1
PE_LIBSCI_DEFAULT_GENCOMPS_CRAY_x86_64=83
PE_PAPI_DEFAULT_PKGCONFIG_VARIABLES=PE_PAPI_ACCEL_LI
  ↳ BS_@accelerator@
PE_PETSC_DEFAULT_GENCOMPILERS_CRAY_haswell=8.6
PE_PETSC_DEFAULT_GENCOMPS_GNU_mic_knl=53
PE_PETSC_DEFAULT_GENCOMPS_INTEL_mic_knl=160
PE_TPSL_64_DEFAULT_GENCOMPILERS_GNU_interlagos=5.1
  ↳ 4.9
PE_TPSL_64_DEFAULT_GENCOMPS_INTEL_sandybridge=160
MPICH_DIR=/opt/cray/mpt/7.6.3/gni/mpich-pgi/15.3
PGI_VERS_STR=18.4.0
HOSTTYPE=x86_64
ATP_POST_LINK_OPTS=-Wl,-L/opt/cray/atp/2.1.1/libApp/
PE_FFTW_DEFAULT_REQUIRED_PRODUCTS=PE_MPICH
PE_FFTW_DEFAULT_TARGET_sandybridge=sandybridge
PE_HDF5_PARALLEL_DEFAULT_REQUIRED_PRODUCTS=PE_MPICH
PE_NETCDF_HDF5PARALLEL_DEFAULT_REQUIRED_PRODUCTS=PE_
  ↳ HDF5_PARALLEL:PE_MPICH
PE_PETSC_DEFAULT_GENCOMPILERS_INTEL_sandybridge=16.0
PE_TPSL_64_DEFAULT_GENCOMPILERS_CRAY_haswell=8.6
PE_MPICH_FORTTRAN_PKGCONFIG_LIBS=mpichf90
PBS_WALLTIME=300
PE_PETSC_DEFAULT_GENCOMPILERS_GNU_mic_knl=5.3
RCLOCAL_PRGENV=true
PBS_MOMPORT=15003
PBS_GPUFILE=/var/spool/torque/aux//4642066gpu
FROM_HEADER=
```

```

PE_PRODUCT_LIST=CRAY_PMI:CRAY_LIBSCI:PGI:CRAYPE:CRAY_
↪ PE_INTERLAGOS:CRAY_LLM:CRAY_XPMEM:CRAY_DMAPP:CRA_
↪ Y_UGNI:CRAY_UDREG:CRAY_ALPS
PE_LIBSCI_DEFAULT_GENCOMPILERS_INTEL_x86_64=15.0
PE_LIBSCI_GENCOMPS_INTEL_x86_64=150
PE_TPSSL_DEFAULT_GENCOMPILERS_CRAY_x86_64=8.6
PE_TPSSL_DEFAULT_GENCOMPS_GNU_interlagos=51 49
GCC_VERSION=6.3.0
PAGER=less
PE_MPICH_DEFAULT_GENCOMPS_PGI=153
PE_PETSC_DEFAULT_GENCOMPILERS_GNU_x86_64=5.3 4.9
PE_TPSSL_DEFAULT_GENCOMPS_GNU_x86_skylake=61
CRAY_MPICH_ROOTDIR=/opt/cray/mpt/7.6.3
PGI_VERSION=18.4
ALPS_APP_PE=0
CSHEDIT=emacs
PE_LIBSCI_GENCOMPILERS_GNU_x86_64=6.1 5.1 4.9
PE_PETSC_DEFAULT_GENCOMPS_GNU_skylake=61
PE_PETSC_DEFAULT_GENCOMPS_INTEL_skylake=160
PE_TPSSL_64_DEFAULT_GENCOMPILERS_INTEL_x86_64=16.0
PE_MPICH_GENCOMPILERS_CRAY=8.6
PE_MPICH_MODULE_NAME=cray-mpich
PROJWORK=/lustre/atlas/proj-shared
SPS_HOME=/ccs/home/USER/astro/fsps
PBS_O_QUEUE=debug
XDG_CONFIG_DIRS=/etc/xdg
PE_LIBSCI_DEFAULT_GENCOMPILERS_CRAY_x86_64=8.3
PE_LIBSCI_GENCOMPS_CRAY_x86_64=83
PE_MPICH_DEFAULT_VOLATILE_PRGENV=CRAY GNU PGI
PE_MPICH_TARGET_VAR_nvidia20=-lcudart
PE_TPSSL_64_DEFAULT_REQUIRED_PRODUCTS=PE_MPICH:PE_LIB_
↪ SCI
PE_TPSSL_DEFAULT_GENCOMPS_CRAY_haswell=86
PE_TPSSL_DEFAULT_GENCOMPS_CRAY_sandybridge=86
MINICOM=-c on
USERMODULES=PrgEnv-cray:PrgEnv-gnu:PrgEnv-intel:PrgE_
↪ nv-pathscales:PrgEnv-pgi:acml:alps:apprentice:app_
↪ rentice2:atp:blcr:cce:chapel:cray-cdb:cray-fftw_
↪ :cray-ga:cray-hdf5:cray-hdf5-parallel:cray-lgdb:_
↪ cray-libsci:cray-libsci_acc:cray-mpich:cray-mpic_
↪ h-compat:cray-mpich2:cray-netcdf:cray-netcdf-hdf_
↪ 5parallel:cray-parallel-netcdf:cray-petsc:cray-p_
↪ etsc-complex:cray-shmem:cray-snp-launcher:cray-tp_
↪ sl:cray-trilinos:craypat:craype:craypkg-gen:cuda_
↪ toolkit:ddt:fftw:ga:gcc:hdf5:hdf5-parallel:intel_
↪ :iobuf:java:lgdb:libfast:libsci_acc:mpich1:netcd_
↪ f:netcdf-hdf5parallel:netcdf-nofsync:netcdf-nofs_
↪ ync-hdf5parallel:ntk:onesided:papi:parallel-netc_
↪ df:pathscales:perftools:perftools-lite:petsc:pets_
↪ c-complex:pgi:pmi:stat:totalview:tpsl:trilinos:x_
↪ t-asynce:xt-craypat:xt-lgdb:xt-libsci:xt-mpich2_
↪ :xt-mpt:xt-papi:xt-shmem:xt-totalview
CRAY_DMAPP_INCLUDE_OPTS=-I/opt/cray/dmapp/7.0.1-1.05_
↪ 02.11080.8.74.gem/include
↪ -I/opt/cray/gni-headers/4.0-1.0502.10859.7.8.gem_
↪ /include

```

```

CRAY_LIBSCI_BASE_DIR=/opt/cray/libsci/16.11.1
CRAY_LIBSCI_DIR=/opt/cray/libsci/16.11.1
PE_ACML_DEFAULT_DIR_PGI=pgi64
PE_LIBSCI_ACC_DEFAULT_VOLATILE_PKGCONFIG_PATH=/opt/c_
↪ ray/libsci_acc/18.04.1/@PRGENV@/@PE_LIBSCI_ACC_D_
↪ EFAULT_GENCOMPS@/@PE_LIBSCI_ACC_DEFAULT_TARGET@/_
↪ lib/pkgconfig
PE_LIBSCI_PKGCONFIG_LIBS=libsci_mpi:libsci
PE_NETCDF_DEFAULT_GENCOMPS_GNU=51 49
PE_PARALLEL_NETCDF_DEFAULT_GENCOMPS_GNU=51 49
PE_TPSSL_64_DEFAULT_GENCOMPS_GNU_mic_knl=51
PE_TPSSL_64_DEFAULT_GENCOMPS_GNU_x86_64=51 49
PGI=/opt/pgi/18.4.0
PBS_O_LOGNAME=USER
PATH=/opt/nvidia/cudatoolkit9.1/9.1.85_3.10-1.0502.d_
↪ f1cc54.3.1/bin:/opt/nvidia/cudatoolkit9.1/9.1.85_
↪ _3.10-1.0502.df1cc54.3.1/libnvvp:/opt/gcc/6.3.0/_
↪ bin:/ccs/home/USER/codar/spack/bin:/sw/xk6/bin:/_
↪ sw/xk6/hsi/5.0.2.p1/sles11.5/bin:/autofs/nccs-sv_
↪ m1_sw/titan/.swci/0-login/opt/spack/20170612/lin_
↪ ux-suse_linux11-x86_64/gcc-5.3.0/git-2.13.0-znpq_
↪ lkovoclvt5rwm3rkpk7d2m56ez2/bin:/sw/xk6/xalt/0._
↪ 7.5/bin:/sw/xk6/lustredu/1.4/sles11.3_gnu4.8.2/b_
↪ in:/opt/cray/pmi/5.0.9-1.0000.10911.175.4.gem/bi_
↪ n:/opt/pgi/18.4.0/linux86-64/18.4/bin:/opt/cray/_
↪ mpt/7.6.3/gni/bin:/opt/cray/craype/2.5.13/bin:/o_
↪ pt/cray/llm/default/bin:/opt/cray/llm/default/et_
↪ c:/opt/cray/xpmem/0.1-2.0502.64982.7.26.gem/bin:_
↪ /opt/cray/ugni/6.0-1.0502.10863.8.28.gem/bin:/op_
↪ t/cray/udreg/2.3.2-1.0502.10518.2.17.gem/bin:/op_
↪ t/cray/lustre-cray_gem_s/2.8.2_3.0.101_0.46.1_1._
↪ 0502.8871-1.0502.0.44.1/sbin:/opt/cray/lustre-cr_
↪ ay_gem_s/2.8.2_3.0.101_0.46.1_1.0502.8871-1.0502_
↪ .0.44.1/bin:/opt/cray/alps/5.2.4-2.0502.9950.37._
↪ 1.gem/sbin:/opt/cray/alps/5.2.4-2.0502.9950.37.1_
↪ .gem/bin:/opt/cray/sdb/1.1-1.0502.63652.4.27.gem_
↪ /bin:/opt/cray/nodestat/2.2-1.0502.60539.1.31.ge_
↪ m/bin:/opt/modules/3.2.10.6/bin:/usr/bin:/usr/sb_
↪ in:/opt/roab/bin:/ccs/home/USER/bin:/usr/local/b_
↪ in:/usr/bin:/bin:/usr/bin/X11:/usr/X11R6/bin:/us_
↪ r/games:/opt/bin:/usr/lib/mit/bin:/usr/lib/mit/s_
↪ bin:/usr/lib/qt3/bin:/opt/cray/bin:/opt/bin:/opt_
↪ /public/bin:/opt/bin:/opt/public/bin:/cm/local/a_
↪ pps/environment-modules/3.2.10/bin
MAIL=/var/spool/mail/USER
MODULE_VERSION=3.2.10.6
PE_HDF5_DEFAULT_VOLATILE_PKGCONFIG_PATH=/opt/cray/hd_
↪ f5/1.10.0.3/@PRGENV@/@PE_HDF5_DEFAULT_GENCOMPS@/_
↪ lib/pkgconfig
PE_PKGCONFIG_DEFAULT_PRODUCTS=PE_TRILINOS:PE_TPSSL_64_
↪ :PE_TPSSL:PE_PETSC:PE_PARALLEL_NETCDF:PE_NETCDF_H_
↪ DF5PARALLEL:PE_NETCDF:PE_MPICH:PE_LIBSCI_ACC:PE_
↪ LIBSCI:PE_HDF5_PARALLEL:PE_HDF5:PE_GA:PE_FFTW2:P_
↪ E_FFTW:PE_ACML
PE_TPSSL_DEFAULT_GENCOMPILERS_GNU_x86_64=5.1 4.9
PE_TPSSL_DEFAULT_GENCOMPILERS_PGI_x86_64=15.3

```


Addressing Data Resiliency for Staging Based Scientific Workflows

```
PE_TPSL_DEFAULT_GENCOMPS_CRAY_interlagos=86
PE_MPICH_GENCOMPILERS_GNU=5.1 4.9
APRUN_XFER_LIMITS=0
ALPS_APP_DEPTH=1
PBS_O_LANG=en_US.UTF-8
CPU=x86_64
XTPE_NETWORK_TARGET=gemini
ATP_IGNORE_SIGTERM=1
PE_FFTW_DEFAULT_TARGET_abudhabi=abudhabi
PE_LIBSCI_DEFAULT_GENCOMPS_PGI_x86_64=153
PE_MPICH_DEFAULT_DIR_PGI_DEFAULT64=64
PE_NETCDF_DEFAULT_GENCOMPILERS_GNU=5.1 4.9
PE_PARALLEL_NETCDF_DEFAULT_GENCOMPILERS_GNU=5.1 4.9
PE_PETSC_DEFAULT_GENCOMPS_CRAY_mic_knl=86
PE_TPSL_64_DEFAULT_GENCOMPILERS_GNU_x86_skylake=6.1
PE_TPSL_DEFAULT_GENCOMPILERS_GNU_haswell=5.1 4.9
_=/usr/bin/env
PBS_JOBCOOKIE=6C6A7D68D1D84BD6A3DBD487ECB61906
JAVA_BINDIR=/usr/lib64/jvm/java/bin
PE_HDF5_PARALLEL_DEFAULT_FIXED_PRGENV=CRAY PGI INTEL
PE_HDF5_PARALLEL_DEFAULT_GENCOMPS_GNU=51 49
PE_NETCDF_HDF5PARALLEL_DEFAULT_FIXED_PRGENV=CRAY PGI
↳ INTEL
PE_NETCDF_HDF5PARALLEL_DEFAULT_GENCOMPS_GNU=51 49
PE_SMA_DEFAULT_DIR_CRAY_DEFAULT64=64
PE_TPSL_64_DEFAULT_GENCOMPILERS_CRAY_x86_skylake=8.6
CRAY_UDREG_POST_LINK_OPTS=-L/opt/cray/udreg/2.3.2-1.
↳ 0502.10518.2.17.gem/lib64
PE_LIBSCI_DEFAULT_GENCOMPILERS_INTEL_mic_knl=15.0
PE_LIBSCI_GENCOMPS_INTEL_mic_knl=150
PE_TPSL_64_DEFAULT_GENCOMPS_CRAY_sandybridge=86
PE_TPSL_64_DEFAULT_VOLATILE_PRGENV=CRAY CRAY64 GNU
↳ GNU64 INTEL INTEL64 PGI PGI64
PE_TPSL_DEFAULT_GENCOMPILERS_CRAY_mic_knl=8.6
PE_TPSL_DEFAULT_GENCOMPS_INTEL_interlagos=160
PWD=/lustre/atlas/scratch/USER/csc143/duanspaper
INPUTRC=/etc/inputrc
CRAY_ALPS_POST_LINK_OPTS=-L/opt/cray/alps/5.2.4-2.05
↳ 02.9950.37.1.gem/lib64
CRAYPE_VERSION=2.5.13
PE_TPSL_DEFAULT_GENCOMPS_GNU_mic_knl=51
PE_MPICH_VOLATILE_PRGENV=CRAY GNU PGI
JAVA_HOME=/usr/lib64/jvm/java
```

```
TARGETMODULES=craype-abudhabi:craype-abudhabi-cu:craype-accel-host:craype-accel-nvidia20:craype-accel-nvidia30:craype-accel-nvidia35:craype-barcelona:craype-broadwell:craype-haswell:craype-hugepages128K:craype-hugepages128M:craype-hugepages16M:craype-hugepages256M:craype-hugepages2M:craype-hugepages32M:craype-hugepages4M:craype-hugepages512K:craype-hugepages512M:craype-hugepages64M:craype-hugepages8M:craype-intel-knc:craype-interlagos:craype-interlagos-cu:craype-istanbul:craype-ivybridge:craype-mc12:craype-mc8:craype-mic-knl:craype-network-aries:craype-network-gemini:craype-network-infiniband:craype-network-none:craype-network-seastar:craype-sandybridge:craype-shanghai:craype-target-compute_node:craype-target-local_host:craype-target-native:craype-xeon:xtpe-barcelona:xtpe-interlagos:xtpe-interlagos-cu:xtpe-istanbul:xtpe-mc12:xtpe-mc8:xtpe-network-gemini:xtpe-network-seastar:xtpe-shanghai:xtpe-target-native:xtpe-xeon
_LMFILES=/opt/modulefiles/modules/3.2.10.6:/opt/cray/modulefiles/nodestat/2.2-1.0502.60539.1.31.gem:/opt/cray/gem/modulefiles/sdb/1.1-1.0502.63652.4.27.gem:/opt/cray/gem/modulefiles/alps/5.2.4-2.0502.9950.37.1.gem:/opt/cray/gem/modulefiles/lustre-cray_gem_s/2.8.2_3.0.101_0.46.1_1.0502.871-1.0502.0.44.1:/opt/cray/gem/modulefiles/udreg/2.3.2-1.0502.10518.2.17.gem:/opt/cray/gem/modulefiles/ugni/6.0-1.0502.10863.8.28.gem:/opt/cray/gem/modulefiles/gni-headers/4.0-1.0502.10859.9.26.gem:/opt/cray/gem/modulefiles/dmapp/7.0.1-1.0502.11080.8.74.gem:/opt/cray/gem/modulefiles/xpmm/0.1-2.0502.64982.7.26.gem:/opt/modulefiles/hs-s-llm/7.2.0:/opt/modulefiles/Base-opts/1.0.2-1.0502.60680.2.4.gem:/opt/modulefiles/pgi/18.4.0:/opt/cray/craype/2.5.13/modulefiles/craype-network-gemini:/opt/cray/craype/2.5.13/modulefiles/craype-interlagos:/opt/cray/modulefiles/craype/2.5.13:/opt/cray/modulefiles/cray-mpich/7.6.3:/opt/cray/modulefiles/cray-libsci/16.11.1:/opt/cray/gem/modulefiles/pmi/5.0.9-1.0000.10911.175.4.gem:/opt/cray/modulefiles/atp/2.1.1:/opt/cray/modulefiles/PrgEnv-pgi/5.2.82:/sw/xk6/modulefiles/lustredu/1.4:/sw/xk6/modulefiles/xalt/0.7.5:/sw/xk6/modulefiles/git/2.13.0:/sw/xk6/modulefiles/module_msg/0.1:/sw/xk6/modulefiles/modulator/1.2.0:/sw/xk6/modulefiles/hsi/5.0.2.p1:/sw/xk6/modulefiles/DefApps:/opt/modulefiles/gcc/6.3.0:/opt/cray/modulefiles/cudatoolkit/9.1.85_3.10-1.0502.df1cc54.3.1
PE_LIBSCI_DEFAULT_GENCOMPS_INTEL_mic_knl=150
PE_LIBSCI_DEFAULT_OMP_REQUIRES=
PE_MPICH_DEFAULT_GENCOMPS_CRAY=86
PE_PETSC_DEFAULT_GENCOMPILERS_GNU_sandybridge=5.3 4.9
PE_TPSL_DEFAULT_GENCOMPILERS_INTEL_haswell=16.0
PE_LIBSCI_ACC_DEFAULT_NV_SUFFIX_nvidia20=nv20
```

```

PE_LIBSCI_MODULE_NAME=cray-libsci/16.11.1
PE_PETSC_DEFAULT_GENCOMPILERS_CRAY_skylake=8.6
PE_TPSSL_DEFAULT_GENCOMPILERS_CRAY_interlagos=8.6
PE_TPSSL_DEFAULT_GENCOMPILERS_GNU_mic_knl=5.1
PBS_NODENUM=0
LANG=en_US.UTF-8
PE_LIBSCI_DEFAULT_GENCOMPILERS_PGI_x86_64=15.3
PE_LIBSCI_GENCOMPS_PGI_x86_64=153
PE_TPSSL_64_DEFAULT_GENCOMPS_GNU_x86_skylake=61
PE_INTEL_FIXED_PKGCONFIG_PATH=/opt/cray/mpt/7.6.3/gn
↳ i/mpich-intel/16.0/lib/pkgconfig
PGROUPD_LICENSE_FILE=/opt/pgi/license.dat
SYSTEM_USERDIR=/tmp/work/USER
MOABHOMEDIR=/opt/moab
PYTHONSTARTUP=/etc/pythonstart
MODULEPATH=/opt/cray/craype/2.5.13/modulefiles:/opt/
↳ cray/gem/modulefiles:/opt/cray/modulefiles:/opt/
↳ modulefiles:/sw/xk6/modulefiles:/sw/xk7/modulefi
↳ les:/lustre/atlas/scratch/USER/csc242/sw/titan/m
↳ odulefiles:/ccs/proj/env003/jyc/titan/sw/modulef
↳ iles:/lustre/atlas/world-shared/csc143/jyc/titan
↳ /sw/modulefiles:/ccs/home/USER/modulefiles
PE_ACML_DEFAULT_VOLATILE_PKGCONFIG_PATH=/opt/acml/5.
↳ 3.1/@PE_ACML_DEFAULT_DIR@PE_ACML_DEFAULT_TARGET
↳ @@PE_ACML_DEFAULT_DIR_OPENMP@PE_ACML_DEFAULT_DI
↳ R_DEFAULT64@/lib/pkgconfig
PE_LIBSCI_GENCOMPILERS_CRAY_x86_64=8.3
PE_MPICH_NV_LIBS_nvidia20--lcudart
PE_MPICH_VOLATILE_PKGCONFIG_PATH=/opt/cray/mpt/7.6.3
↳ /gni/mpich-@PRGENV@PE_MPICH_DIR_DEFAULT64@PE_
↳ MPICH_GENCOMPS@/lib/pkgconfig
PBS_NUM_NODES=1
SDK_HOME=/usr/lib64/jvm/java
LOADED_MODULES=modules/3.2.10.6:nodestat/2.2-1.0502.6
↳ 0539.1.31.gem:sdb/1.1-1.0502.63652.4.27.gem:alps
↳ /5.2.4-2.0502.9950.37.1.gem:lustre-cray_gem_s/2.
↳ 8.2_3.0.101_0.46.1_1.0502.8871-1.0502.0.44.1:udr
↳ eg/2.3.2-1.0502.10518.2.17.gem:ugni/6.0-1.0502.1
↳ 0863.8.28.gem:gni-headers/4.0-1.0502.10859.9.26.
↳ gem:dmapp/7.0.1-1.0502.11080.8.74.gem:xpmem/0.1-
↳ 2.0502.64982.7.26.gem:hss-llm/7.2.0:Base-opts/1.
↳ 0.2-1.0502.60680.2.4.gem:pgi/18.4.0:craype-netwo
↳ rk-gemini:craype-interlagos:craype/2.5.13:cray-m
↳ pich/7.6.3:cray-libsci/16.11.1:pmi/5.0.9-1.0000.
↳ 10911.175.4.gem:atp/2.1.1:PrgEnv-pgi/5.2.82:lust
↳ redu/1.4:xalt/0.7.5:git/2.13.0:module_msg/0.1:mo
↳ dulator/1.2.0:hsi/5.0.2.pl:DefApps:gcc/6.3.0:cud
↳ atoolkit/9.1.85_3.10-1.0502.df1cc54.3.1
SHMEM_ABORT_ON_ERROR=1
OLCF_GIT_ROOT=/autofs/nccs-svm1_sw/titan/.swci/0-log
↳ in/opt/spack/20170612/linux-suse_linux11-x86_64/
↳ gcc-5.3.0/git-2.13.0-znpqlkovoclvt5rwm3rkpk7d2m
↳ 56ez2
CRAY_PORTALS_USE_BLOCKING_POLL=no
CRAY_DMAPP_POST_LINK_OPTS=-L/opt/cray/dmapp/7.0.1-1.
↳ 0502.11080.8.74.gem/lib64

```

```

PE_FFTW_DEFAULT_TARGET_ivybridge=ivybridge
PE_FFTW_DEFAULT_TARGET_share=share
PE_FFTW_DEFAULT_TARGET_x86_skylake=x86_skylake
PE_PKG_CONFIG_PATH=/opt/cray/cti/1.0.6/lib/pkgconfig
↳ :/opt/cray/cti/1.0.4/lib/pkgconfig:/opt/cray/cti
↳ /1.0.1/lib/pkgconfig
PE_TPSSL_64_DEFAULT_GENCOMPS_GNU_interlagos=51 49
PE_TPSSL_DEFAULT_GENCOMPILERS_INTEL_mic_knl=16.0
PE_TPSSL_DEFAULT_GENCOMPS_PGI_x86_64=153
PBS_0_SHELL=/bin/bash
PE_LIBSCI_OMP_REQUIRES_openmp=_mp
PE_PETSC_DEFAULT_GENCOMPILERS_GNU_skylake=6.1
PE_TPSSL_DEFAULT_GENCOMPILERS_CRAY_x86_skylake=8.6
PE_TPSSL_64_DEFAULT_GENCOMPS_CRAY_mic_knl=86
PE_TPSSL_DEFAULT_GENCOMPILERS_INTEL_x86_64=16.0
CRAY_MPICH_DIR=/opt/cray/mpt/7.6.3/gni/mpich-pgi/15.3
PE_MPICH_CXX_PKGCONFIG_LIBS=mpichcxx
PBS_JOBID=4642066
PE_LIBSCI_ACC_DEFAULT_GENCOMPILERS_GNU_x86_64=4.9
PE_LIBSCI_DEFAULT_GENCOMPS_INTEL_x86_64=150
PE_MPICH_PKGCONFIG_VARIABLES=PE_MPICH_NV_LIBS@accel
↳ erator@:PE_MPICH_ALTERNATE_LIBS@multithreaded@:
↳ PE_MPICH_ALTERNATE_LIBS@dpm@
ENVIRONMENT=BATCH
CRAY_PMI_POST_LINK_OPTS=-L/opt/cray/pmi/5.0.9-1.0000
↳ .10911.175.4.gem/lib64
PE_HDF5_DEFAULT_FIXED_PRGENV=CRAY PGI INTEL
PE_TPSSL_64_DEFAULT_GENCOMPILERS_CRAY_mic_knl=8.6
PE_TPSSL_DEFAULT_GENCOMPILERS_INTEL_x86_skylake=16.0
PE_TPSSL_DEFAULT_VOLATILE_PKGCONFIG_PATH=/opt/cray/tp
↳ sl/17.11.1/@PRGENV@PE_TPSSL_DEFAULT_GENCOMPS@/
↳ PE_TPSSL_DEFAULT_TARGET@/lib/pkgconfig
CRAY_MPICH2_VER=7.6.3
PE_MPICH_PKGCONFIG_LIBS=mpich
WORLDWORK=/lustre/atlas/world-shared
PE_GA_DEFAULT_GENCOMPILERS_GNU=5.1 4.9
PE_LIBSCI_ACC_DEFAULT_GENCOMPS_GNU_x86_64=49
PE_LIBSCI_VOLATILE_PKGCONFIG_PATH=/opt/cray/libsci/1
↳ 6.11.1/@PRGENV@PE_LIBSCI_GENCOMPS@PE_LIBSCI_
↳ TARGET@/lib/pkgconfig
PE_MPICH_ALTERNATE_LIBS_multithreaded=_mt
PE_NETCDF_DEFAULT_FIXED_PRGENV=CRAY PGI INTEL
PE_PARALLEL_NETCDF_DEFAULT_FIXED_PRGENV=CRAY PGI
↳ INTEL
PE_TPSSL_DEFAULT_GENCOMPS_PGI_interlagos=153
CUDAToolkit_HOME=/opt/nvidia/cudatoolkit9.1/9.1.85_3
↳ .10-1.0502.df1cc54.3.1
HOME=/ccs/home/USER
SHLVL=4
JDK_HOME=/usr/lib64/jvm/java
QT_SYSTEM_DIR=/usr/share/desktop-data
CRAY_LIBSCI_VERSION=16.11.1
PE_HDF5_PARALLEL_DEFAULT_VOLATILE_PRGENV=GNU
PE_MPICH_TARGET_VAR_nvidia35=-lcudart
PE_NETCDF_HDF5PARALLEL_DEFAULT_VOLATILE_PRGENV=GNU
PE_PKGCONFIG_PRODUCTS_DEFAULT=PE_PAPI

```

Addressing Data Resiliency for Staging Based Scientific Workflows

```
PE_TPSL_64_DEFAULT_GENCOMPS_GNU_haswell=51 49
MEMBERWORK=/lustre/atlas/scratch/USER
OLCF_MODULATOR_SESSION=1554915651.4094.titan-batch3.
↪ ccs.ornl.gov
OSTYPE=linux
LESS_ADVANCED_PREPROCESSOR=no
PE_LIBSCI_GENCOMPILERS_PGI_x86_64=15.3
PE_TPSL_DEFAULT_GENCOMPILERS_INTEL_interlagos=16.0
PGI_PATH=/opt/pgi/18.4.0
PE_ACML_DEFAULT_DIR_OPENMP=_mp
PE_LIBSCI_ACC_DEFAULT_NV_SUFFIX_nvidia60=nv60
PE_MPICH_DEFAULT_VOLATILE_PKGCONFIG_PATH=/opt/cray/m
↪ pt/7.6.3/gni/mpich-@PRGENV@PE_MPICH_DEFAULT_DIR
↪ _DEFAULT64@PE_MPICH_DEFAULT_GENCOMPS@lib/pkgc
↪ onfig
PE_PETSC_DEFAULT_GENCOMPILERS_CRAY_interlagos=8.6
PE_TPSL_DEFAULT_VOLATILE_PRGENV=CRAY CRAY64 GNU GNU64
↪ INTEL INTEL64 PGI PGI64
OLCF_MODULE_MSG=/sw/sources/module_msg/0.1
PBS_O_HOST=titan-ext3.ccs.ornl.gov
XCURSOR_THEME=crystalwhite
LS_OPTIONS=-N --color=none -T 0
CRAY_PMI_INCLUDE_OPTS=-I/opt/cray/pmi/5.0.9-1.0000.1
↪ 0911.175.4.gem/include
PE_TPSL_64_DEFAULT_GENCOMPS_CRAY_interlagos=86
PE_TPSL_DEFAULT_GENCOMPS_INTEL_sandybridge=160
CRAY_CUDAToolKIT_INCLUDE_OPTS=-I/opt/nvidia/cudatool
↪ kit9.1/9.1.85_3.10-1.0502.df1cc54.3.1/include
↪ -I/opt/nvidia/cudatoolkit9.1/9.1.85_3.10-1.0502.
↪ df1cc54.3.1/extras/CUPTI/include
↪ -I/opt/nvidia/cudatoolkit9.1/9.1.85_3.10-1.0502.
↪ df1cc54.3.1/extras/Debugger/include
CRAY_CUDAToolKIT_DIR=/opt/nvidia/cudatoolkit9.1/9.1.
↪ 85_3.10-1.0502.df1cc54.3.1
WINDOWMANAGER=
PRGENVMODULES=PrgEnv-cray:PrgEnv-gnu:PrgEnv-intel:Pr
↪ gEnv-pathscales:PrgEnv-pgi
CRAY_LLM_DIR=/opt/cray/llm/default
CRAYPE_NETWORK_TARGET=gemini
ATP_MRNET_COMM_PATH=/opt/cray/atp/2.1.1/libexec/atp_
↪ mrnet_commnnode_wrapper
PE_TPSL_DEFAULT_GENCOMPILERS_CRAY_haswell=8.6
PKG_CONFIG_PATH_DEFAULT=/opt/cray/papi/5.6.0.2/lib64
↪ /pkgconfig
PE_MPICH_DIR_CRAY_DEFAULT64=64
GCC_PATH=/opt/gcc/6.3.0
PBS_VNODENUM=0
PE_LIBSCI_GENCOMPILERS_INTEL_mic_knl=15.0
PE_PETSC_DEFAULT_GENCOMPILERS_GNU_haswell=5.3 4.9
PE_TPSL_64_DEFAULT_GENCOMPILERS_GNU_mic_knl=5.1
PE_TPSL_DEFAULT_GENCOMPILERS_GNU_interlagos=5.1 4.9
PE_TPSL_DEFAULT_GENCOMPILERS_INTEL_sandybridge=16.0
PE_TPSL_DEFAULT_GENCOMPILERS_PGI_interlagos=15.3
LOGNAME=USER
MACHTYPE=x86_64-suse-linux
LESS=-M -I
```

```
G_FILENAME_ENCODING=@locale,UTF-8,ISO-8859-15,CP1252
CRAY_GNI_HEADERS_INCLUDE_OPTS=-I/opt/cray/gni-header
↪ s/4.0-1.0502.10859.9.26.gem/include
PYTHONPATH=/sw/xk6/xalt/0.7.5/site:/sw/xk6/xalt/0.7.
↪ 5/libexec:/opt/cray/sdb/1.1-1.0502.63652.4.27.ge
↪ m/lib64/py:/ccs/home/USER/.local/summit/anaconda
↪ 3/5.3.0/3.6/lib/python3.6/site-packages
CRAY_LIBSCI_PREFIX_DIR=/opt/cray/libsci/16.11.1/PGI/
↪ 15.3/x86_64
PE_HDF5_DEFAULT_GENCOMPS_GNU=51 49
PE_MPICH_NV_LIBS=
PE_NETCDF_DEFAULT_REQUIRED_PRODUCTS=PE_HDF5
PE_TPSL_64_DEFAULT_GENCOMPILERS_GNU_haswell=5.1 4.9
PE_TPSL_64_DEFAULT_GENCOMPILERS_INTEL_sandybridge=16
↪ .0
PE_TPSL_DEFAULT_GENCOMPS_GNU_x86_64=51 49
PE_TRILINOS_DEFAULT_REQUIRED_PRODUCTS=PE_MPICH:PE_HD
↪ F5_PARALLEL:PE_NETCDF_HDF5PARALLEL:PE_LIBSCI:PE_
↪ TPSL
CVS_RSH=ssh
DMAPP_ABORT_ON_ERROR=1
PE_LIBSCI_OMP_REQUIRES=
PE_MPICH_DEFAULT_GENCOMPILERS_CRAY=8.6
PE_TRILINOS_DEFAULT_GENCOMPS_GNU_x86_64=51 49
PE_MPICH_GENCOMPS_CRAY=86
PBS_QUEUE=debug
XDG_DATA_DIRS=/usr/local/share:/usr/share:/etc/opt/k
↪ de3/share:/opt/kde3/share
TOOLMODULES=apprentice:apprentice2:atp:chapel:cray-l
↪ gdb:cray-snp launcher:craypat:craypkg-gen:ddt:gdb
↪ :iobuf:papi:perftools:perftools-lite:stat:totalv
↪ iew:xt-craypat:xt-lgdb:xt-papi:xt-totalview
PE_LIBSCI_ACC_DEFAULT_GENCOMPILERS_CRAY_x86_64=8.5
PE_LIBSCI_ACC_DEFAULT_NV_SUFFIX_nvidia35=nv35
PE_LIBSCI_DEFAULT_REQUIRED_PRODUCTS=PE_MPICH
PE_MPICH_DEFAULT_FIXED_PRGENV=INTEL
PE_MPICH_DEFAULT_GENCOMPS_GNU=51 49
PE_TPSL_64_DEFAULT_GENCOMPILERS_INTEL_interlagos=16.0
PE_TPSL_DEFAULT_GENCOMPILERS_CRAY_sandybridge=8.6
MODULESHOME=/opt/modules/3.2.10.6
PE_FFTW2_DEFAULT_REQUIRED_PRODUCTS=PE_MPICH
PE_GA_DEFAULT_FIXED_PRGENV=CRAY PGI INTEL
PE_LIBSCI_DEFAULT_VOLATILE_PKGCONFIG_PATH=/opt/cray/
↪ libsci/16.11.1/@PRGENV@PE_LIBSCI_DEFAULT_GENCO
↪ MPS@PE_LIBSCI_DEFAULT_TARGET@lib/pkgconfig
PE_TPSL_DEFAULT_GENCOMPILERS_GNU_sandybridge=5.1 4.9
PBS_O_MAIL=/var/mail/USER
PBS_MICFILE=/var/spool/torque/aux//4642066mic
LESSOPEN=lessopen.sh %s
```

```

PKG_CONFIG_PATH=/opt/nvidia/cudatoolkit9.1/9.1.85_3.
  ↪ 10-1.0502.df1cc54.3.1/lib64/pkgconfig:/opt/cray/
  ↪ rca/1.0.0-2.0502.60530.1.63.gem/lib64/pkgconfig:
  ↪ /opt/cray/pmi/5.0.9-1.0000.10911.175.4.gem/lib64
  ↪ /pkgconfig:/opt/cray/craype/2.5.13/pkg-config:/o
  ↪ pt/cray/iobuf/2.0.8/lib/pkgconfig:/opt/cray/fftw
  ↪ /2.1.5.8/lib/pkgconfig:/opt/cray/xpmem/0.1-2.050
  ↪ 2.64982.7.26.gem/lib64/pkgconfig:/opt/cray/dmapp
  ↪ /7.0.1-1.0502.11080.8.74.gem/lib64/pkgconfig:/op
  ↪ t/cray/gni-headers/4.0-1.0502.10859.9.26.gem/lib
  ↪ 64/pkgconfig:/opt/cray/ugni/6.0-1.0502.10863.8.2
  ↪ 8.gem/lib64/pkgconfig:/opt/cray/udreg/2.3.2-1.05
  ↪ 02.10518.2.17.gem/lib64/pkgconfig:/opt/cray/alps
  ↪ /5.2.4-2.0502.9950.37.1.gem/lib64/pkgconfig:/opt
  ↪ /cray/atp/2.1.1/lib/pkgconfig:/ccs/home/USER/sum
  ↪ mit/sw/libfabric/lib/pkgconfig
PE_MPICH_NV_LIBS_nvidia35=-lcudart
PE_PETSC_DEFAULT_VOLATILE_PKGCONFIG_PATH=/opt/cray/p
  ↪ etsc/3.7.6.3/complex/@PRGENV@/PE_PETSC_DEFAULT_
  ↪ GENCOMPS@/PE_PETSC_DEFAULT_TARGET@/lib/pkgconfig
PELOCAL_PRGENV=true
LIBSCI_BASE_DIR=/opt/cray/libsci/16.11.1
PE_TPSSL_64_DEFAULT_GENCOMPS_INTEL_x86_64=160
INFOPATH=/opt/gcc/6.3.0/snos/share/info:/usr/local/i
  ↪ nfo:/usr/share/info:/usr/info
LIBSCI_VERSION=16.11.1
PE_LIBSCI_DEFAULT_PKGCONFIG_VARIABLES=PE_LIBSCI_DEFA
  ↪ ULT_OMP_REQUIRES=@openmp@
PE_MPICH_NV_LIBS_nvidia60=-lcudart
PE_TPSSL_64_DEFAULT_GENCOMPS_GNU_sandybridge=51 49
PE_TPSSL_DEFAULT_GENCOMPS_INTEL_mic_knl=160
PBS_NP=16
CRAY_ALPS_INCLUDE_OPTS=-I/opt/cray/alps/5.2.4-2.0502
  ↪ .9950.37.1.gem/include
CRAY_PRE_COMPILE_OPTS=-hnetwork=gemini
PE_FFTW_DEFAULT_TARGET_broadwell=broadwell
PE_LIBSCI_GENCOMPILERS_INTEL_x86_64=15.0
PE_PGI_DEFAULT_FIXED_PKGCONFIG_PATH=/opt/cray/parall
  ↪ el-netcdf/1.8.1.3/PGI/15.3/lib/pkgconfig:/opt/cr
  ↪ ay/netcdf-hdf5parallel/4.4.1.1.3/PGI/15.3/lib/pk
  ↪ gconfig:/opt/cray/netcdf/4.4.1.1.3/PGI/15.3/lib/
  ↪ pkgconfig:/opt/cray/hdf5-parallel/1.10.0.3/PGI/1
  ↪ 5.3/lib/pkgconfig:/opt/cray/hdf5/1.10.0.3/PGI/15
  ↪ .3/lib/pkgconfig:/opt/cray/ga/5.3.0.7/PGI/15.3/1
  ↪ ib/pkgconfig
PE_TPSSL_64_DEFAULT_GENCOMPILERS_GNU_x86_64=5.1 4.9
CRAY_CPU_TARGET=interlagos
CMAKE_PREFIX_PATH=/autofs/nccs-svm1_sw/titan/.swci/0
  ↪ -login/opt/spack/20170612/linux-suse_linux11-x86_
  ↪ 64/gcc-5.3.0/git-2.13.0-znpqlkovoclvlt5rwm3rpk7
  ↪ d2m56ez2/
XTPE_LINK_TYPE=dynamic
PBS_O_SERVER=titan-moab.ccs.ornl.gov
PBS_NUM_PPN=16
CRAY_UGNI_INCLUDE_OPTS=-I/opt/cray/ugni/6.0-1.0502.1
  ↪ 0863.8.28.gem/include

```

```

CRAY_XPMEM_INCLUDE_OPTS=-I/opt/cray/xpmem/0.1-2.0502
  ↪ .64982.7.26.gem/include
PE_LIBSCI_DEFAULT_GENCOMPS_CRAY_mic_knl=85
PE_LIBSCI_REQUIRED_PRODUCTS=PE_MPICH
PE_MPICH_DEFAULT_GENCOMPILERS_PGI=15.3
PE_PAPI_DEFAULT_ACCELL_FAMILY_LIBS=
PE_TPSSL_64_DEFAULT_GENCOMPS_CRAY_x86_64=86
PE_MPICH_GENCOMPS_PGI=153
PE_LIBSCI_DEFAULT_GENCOMPILERS_GNU_mic_knl=5.1
PE_LIBSCI_DEFAULT_GENCOMPILERS_GNU_x86_64=6.1 5.1 4.9
PE_LIBSCI_GENCOMPS_GNU_mic_knl=51
PE_LIBSCI_GENCOMPS_GNU_x86_64=61 51 49
PE_TPSSL_DEFAULT_GENCOMPS_INTEL_haswell=160
LESSCLOSE=lessclose.sh %s %s
ATP_HOME=/opt/cray/atp/2.1.1
PE_FFTW_DEFAULT_TARGET_x86_64=x86_64
PE_PETSC_DEFAULT_GENCOMPILERS_INTEL_x86_64=16.0
PBS_NODEFILE=/var/spool/torque/aux//4642066
G_BROKEN_FILENAMES=1
CRAY_LD_LIBRARY_PATH=/opt/nvidia/cudatoolkit9.1/9.1.
  ↪ 85_3.10-1.0502.df1cc54.3.1/lib64:/opt/nvidia/cud
  ↪ atoolkit9.1/9.1.85_3.10-1.0502.df1cc54.3.1/extra
  ↪ s/CUPTI/lib64:/opt/cray/pmi/5.0.9-1.0000.10911.1
  ↪ 75.4.gem/lib64:/opt/cray/libsci/16.11.1/PGI/15.3
  ↪ /x86_64/lib:/opt/cray/mpt/7.6.3/gni/mpich-pgi/15
  ↪ .3/lib:/opt/cray/xpmem/0.1-2.0502.64982.7.26.gem
  ↪ /lib64:/opt/cray/dmapp/7.0.1-1.0502.11080.8.74.g
  ↪ em/lib64:/opt/cray/ugni/6.0-1.0502.10863.8.28.ge
  ↪ m/lib64:/opt/cray/udreg/2.3.2-1.0502.10518.2.17.
  ↪ gem/lib64:/opt/cray/alps/5.2.4-2.0502.9950.37.1.
  ↪ gem/lib64
CRAYOS_VERSION=5.2.82
PE_FFTW_DEFAULT_TARGET_haswell=haswell
PE_GA_DEFAULT_GENCOMPS_GNU=51 49
PE_GA_DEFAULT_VOLATILE_PKGCONFIG_PATH=/opt/cray/ga/5
  ↪ .3.0.7/@PRGENV@/PE_GA_DEFAULT_GENCOMPS@/lib/pkg
  ↪ config
PE_INTEL_DEFAULT_FIXED_PKGCONFIG_PATH=/opt/cray/para
  ↪ llel-netcdf/1.8.1.3/INTEL/16.0/lib/pkgconfig:/op
  ↪ t/cray/netcdf-hdf5parallel/4.4.1.1.3/INTEL/16.0/
  ↪ lib/pkgconfig:/opt/cray/netcdf/4.4.1.1.3/INTEL/1
  ↪ 6.0/lib/pkgconfig:/opt/cray/mpt/7.6.3/gni/mpich-
  ↪ intel/16.0/lib/pkgconfig:/opt/cray/hdf5-parallel
  ↪ /1.10.0.3/INTEL/16.0/lib/pkgconfig:/opt/cray/hdf
  ↪ 5/1.10.0.3/INTEL/16.0/lib/pkgconfig:/opt/cray/ga
  ↪ /5.3.0.7/INTEL/15.0/lib/pkgconfig
PE_PAPI_DEFAULT_ACCEL_LIBS=
PE_PETSC_DEFAULT_GENCOMPILERS_GNU_interlagos=5.3 4.9
PE_PETSC_DEFAULT_GENCOMPILERS_INTEL_haswell=16.0
PE_SMA_DEFAULT_DIR_PGI_DEFAULT64=64
PE_TPSSL_64_DEFAULT_GENCOMPILERS_INTEL_x86_skylake=16
  ↪ .0

```


Addressing Data Resiliency for Staging Based Scientific Workflows

```
PBS_0_PATH=/opt/nvidia/cudatoolkit9.1/9.1.85_3.10-1.
↪ 0502.df1cc54.3.1/bin:/opt/nvidia/cudatoolkit9.1/
↪ 9.1.85_3.10-1.0502.df1cc54.3.1/libnvvp:/opt/gcc/
↪ 6.3.0/bin:/ccs/home/USER/codar/spack/bin:/sw/xk6
↪ /bin:/sw/xk6/hsi/5.0.2.p1/sles11.5/bin:/autofs/n
↪ ccs-svm1_sw/titan/.swci/0-login/opt/spack/201706
↪ 12/linux-suse_linux11-x86_64/gcc-5.3.0/git-2.13.
↪ 0-znpqlkovoclvt5rwm3rpk7d2m56ez2/bin:/sw/xk6/x
↪ alt/0.7.5/bin:/sw/xk6/lustredu/1.4/sles11.3_gnu4
↪ .8.2/bin:/opt/cray/mpt/7.6.3/gni/bin:/opt/cray/r
↪ ca/1.0.0-2.0502.60530.1.63.gem/bin:/opt/cray/alp
↪ s/5.2.4-2.0502.9774.31.12.gem/sbin:/opt/cray/dvs
↪ /2.5_0.9.0-1.0502.2188.1.113.gem/bin:/opt/cray/x
↪ pmem/0.1-2.0502.64982.5.3.gem/bin:/opt/cray/ugni
↪ /6.0-1.0502.10863.8.28.gem/bin:/opt/cray/udreg/2
↪ .3.2-1.0502.10518.2.17.gem/bin:/opt/cray/craype/
↪ 2.5.13/bin:/opt/pgi/18.4.0/linux86-64/18.4/bin:/
↪ opt/cray/eslogin/eswrap/1.3.3-1.020200.1280.0/bi
↪ n:/usr/bin:/usr/sbin:/opt/moab/bin:/ccs/home/USE
↪ R/bin:/usr/local/bin:/usr/bin:/bin:/usr/bin/X11:
↪ /usr/X11R6/bin:/usr/games:/opt/bin:/usr/lib/mit/
↪ bin:/usr/lib/mit/sbin:/sbin:/usr/sbin:/usr/lib/q
↪ t3/bin:/opt/cray/bin:/opt/bin:/opt/public/bin:/o
↪ pt/bin:/opt/public/bin:/cm/local/apps/enviromen
↪ t-modules/3.2.10/bin
COLORTERM=1
JAVA_ROOT=/usr/lib64/jvm/java
PE_MPICH_DEFAULT_DIR_CRAY_DEFAULT64=64
PE_PETSC_DEFAULT_GENCOMPS_CRAY_haswell=86
PE_PETSC_DEFAULT_GENCOMPS_GNU_x86_64=53 49
PE_PETSC_DEFAULT_GENCOMPS_INTEL_x86_64=160
PE_TPSL_64_DEFAULT_GENCOMPS_PGI_interlagos=153
BASH_FUNC_module()=( ) { eval
↪ ` /opt/modules/3.2.10.6/bin/modulecmd bash $*`
}
+ lsb_release -a
LSB Version:      core-2.0-noarch:core-3.2-noarch:
↪ core-4.0-noarch:core-2.0-x86_64:core-3.2-x86_64:
↪ core-4.0-x86_64:desktop-4.0-amd64:desktop-4.0-no
↪ arch:graphics-2.0-amd64:graphics-2.0-noarch:grap
↪ hics-3.2-amd64:graphics-3.2-noarch:graphics-4.0-
↪ amd64:graphics-4.0-noarch
Distributor ID:   SUSE LINUX
Description:      SUSE Linux Enterprise Server 11
↪ (x86_64)
Release:          11
Codename:         n/a
+ uname -a
Linux nid03772 3.0.101-0.46.1_1.0502.8871-cray_gem_c
↪ #1 SMP Mon Feb 4 22:33:39 UTC 2019 x86_64 x86_64
↪ x86_64 GNU/Linux
+ lscpu
Architecture:     x86_64
CPU op-mode(s):   32-bit, 64-bit
Byte Order:       Little Endian
CPU(s):           16
```

```
On-line CPU(s) list: 0-15
Thread(s) per core: 2
Core(s) per socket: 8
Socket(s):         1
NUMA node(s):      2
Vendor ID:          AuthenticAMD
CPU family:         21
Model:              1
Stepping:           2
CPU MHz:            2200.000
BogoMIPS:           4400.00
Virtualization:     AMD-V
L1d cache:          16K
L1i cache:          64K
L2 cache:           2048K
L3 cache:           6144K
NUMA node0 CPU(s): 0-7
NUMA node1 CPU(s): 8-15
+ cat /proc/meminfo
MemTotal:           33083668 kB
MemFree:            30819880 kB
Buffers:             0 kB
Cached:              60484 kB
SwapCached:         0 kB
Active:              25556 kB
Inactive:            319636 kB
Active(anon):        22032 kB
Inactive(anon):      700 kB
Active(file):         3524 kB
Inactive(file):      318936 kB
Unevictable:         68620 kB
Mlocked:             21128 kB
SwapTotal:           0 kB
SwapFree:            0 kB
Dirty:               0 kB
Writeback:           0 kB
AnonPages:           40368 kB
Mapped:              5972 kB
Shmem:               624 kB
Slab:                732992 kB
SReclaimable:        6024 kB
SUnreclaim:          726968 kB
KernelStack:         2160 kB
PageTables:          1012 kB
NFS_Unstable:        0 kB
Bounce:              0 kB
WritebackTmp:        0 kB
CommitLimit:         16541832 kB
Committed_AS:        74408 kB
VmallocTotal:        34359738367 kB
VmallocUsed:          3916960 kB
VmallocChunk:        34354632735 kB
HugePages_Total:     0
HugePages_Free:      0
HugePages_Rsvd:      0
HugePages_Surp:      0
Hugepagesize:        2048 kB
```

```

DirectMap4k:      3803136 kB
DirectMap2M:      29751296 kB
DirectMap1G:       0 kB
+ lsblk -a
NAME MAJ:MIN RM SIZE RO MOUNTPOINT
ram0  1:0    0  4M  0
ram1  1:1    0  4M  0
ram2  1:2    0  4M  0
ram3  1:3    0  4M  0
ram4  1:4    0  4M  0
ram5  1:5    0  4M  0
ram6  1:6    0  4M  0
ram7  1:7    0  4M  0
ram8  1:8    0  4M  0
ram9  1:9    0  4M  0
ram10 1:10   0  4M  0
ram11 1:11   0  4M  0
ram12 1:12   0  4M  0
ram13 1:13   0  4M  0
ram14 1:14   0  4M  0
ram15 1:15   0  4M  0
loop0 7:0     0    0
loop1 7:1     0    0
loop2 7:2     0    0
loop3 7:3     0    0
loop4 7:4     0    0
loop5 7:5     0    0
loop6 7:6     0    0
loop7 7:7     0    0
+ lsscsi -s
+ module list
++ /opt/modules/3.2.10.6/bin/modulecmd bash list
Currently Loaded Modulefiles:
  1) modules/3.2.10.6
  2) nodestat/2.2-1.0502.60539.1.31.gem
  3) sdb/1.1-1.0502.63652.4.27.gem
  4) alps/5.2.4-2.0502.9950.37.1.gem
  5) lustre-cray_gem_s/2.8.2_3.0.101_0.46.1_1.0502.8_j
    ↪ 871-1.0502.0.44.1
  6) udreg/2.3.2-1.0502.10518.2.17.gem
  7) ugni/6.0-1.0502.10863.8.28.gem
  8) gni-headers/4.0-1.0502.10859.9.26.gem
  9) dmapp/7.0.1-1.0502.11080.8.74.gem
 10) xpmem/0.1-2.0502.64982.7.26.gem
 11) hss-llm/7.2.0
 12) Base-opts/1.0.2-1.0502.60680.2.4.gem
 13) pgi/18.4.0
 14) craype-network-gemini
 15) craype-interlagos
 16) craype/2.5.13
 17) cray-mpich/7.6.3
 18) cray-libsci/16.11.1
 19) pmi/5.0.9-1.0000.10911.175.4.gem
 20) atp/2.1.1
 21) PrgEnv-pgi/5.2.82
 22) lustredu/1.4

```

```

23) xalt/0.7.5
24) git/2.13.0
25) module_msg/0.1
26) modulator/1.2.0
27) hsi/5.0.2.p1
28) DefApps
29) gcc/6.3.0
30) cudatoolkit/9.1.85_3.10-1.0502.df1cc54.3.1
+ eval

```