An Analysis of netCDF-FastBit Integration and Primitive Spatial-Temporal Operations

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An Analysis of netCDF-FastBit Integration and Primitive Spatial-Temporal Operations

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Abstract

A process allowing for the intuitive use of SQL queries on dense multidimensional data stored in Network Common Data Format (netCDF) files is developed using advanced bitmap indexing provided by the FastBit bitmap indexing tool. A method for netCDF data extraction and FastBit index creation is presented and a geospatial Range and pseudo-KNN search based on the haversine function is implemented via SQL. A two step filtering algorithm is shown to greatly enhance the speed of these geospatial queries, allowing for extremely efficient processing of the netCDF data in bitmap indexed form.

Keywords: netCDF, FastBit, geospatial operations

Chapter 1: Introduction

1.1 Summary

Over the past several decades, scientific advances have led to larger and larger amounts of data becoming available for scientific analysis and study in nearly every field. What might have once been considered a staggering amount of data is now often simply dwarfed by the reams of information gathered on a daily basis via numerous highly advanced sensors throughout the world. Faced with somehow storing this vast quantity of raw scientific data, researchers found that many of the more standard database options available were unsuitable for the style of data they possessed. Thus, a proliferation of scientific data formats have been introduced, many written by the researchers themselves, aimed at somehow storing their data in a compact way. Unfortunately, while ever more advanced devices and processes have allowed for this continuously increasing level of data to be stored efficiently, the ability to analyze and access this data in an easy and reasonable manner has not kept similar pace. These scientific data formats, designed with scientific data in mind, manage to provide compact storage of extremely large amounts of information and a basic format and structure for their contents. However, the retrieval and access of the data contained within is often far more complicated, with few ways to easily extract the data stored within these formats, especially not in a manner familiar to any modern database users.

One of the main hurdles in utilizing an industry standard database solution involves the structure of the data itself. Scientific data is very dissimilar from the kind of data classically assumed within current database research. Scientific data is often extremely multidimensional in nature, with no field suitable for acting as a primary key. Further, there is rarely even a unique combination of fields which can act as a primary key; a unique identifier for a data point may often be formed in numerous different ways, or may simply consist of every field utilized together. These features present large hurdles with the most commonly utilized indexing methods. However these features, taken in conjunction with scientific data's generally static nature, make an uncommon indexing method, bitmap indexing, particularly feasible.

Bitmap indexing suffers from several limitations which generally prevent it from being used with regular data. Perhaps the largest of these problems is bitmap indexing’s inefficiency in updating or deleting any of the data records once they have been indexed. The scientific data files being discussed here, however, are generally static in nature, often being written once as the product of a multitude of sensors over a period of time and are otherwise unchanged after creation. Another issue facing bitmap indexing, the cardinality of the data to be indexed, poses more of a problem when utilizing scientific data. As discussed within the term definitions of bitmap indexing and FastBit, however, advances within the field of bitmap indexing have developed many compression algorithms aimed at overcoming this limitation.

As such, the generation of indexes to these scientific data formats utilizing bitmap indexing techniques is proposed. The use of these indexes will allow for rapid, efficient data access within the files in question in a format and method more familiar to many average computer users. As an example of this, the details of a project to utilize the FastBit bitmap indexing suite of tools with netCDF files containing oceanic data are provided. For a one time cost of 25 minutes a reusable bitmap index was created that is capable of answering equality searches over the dataset in 1 second, a 1200x speedup compared to the 20 minutes required to read the entire file. Further, a range query returning all points within a specified distance of a point is implemented via SQL and tested utilizing the generated bitmap index. A two step filter is proposed and implemented, resulting in a large speedup in the range query over a large number of points.

1.2 Defining Terms

The work within this project relies upon several concepts and applications that have come before so an explanation of what and where each of these pieces are is provided in this section. Further, a short history of each term is provided to provide context on the intent and purpose of the idea originally.

1.2.1 What is netCDF?

A shortened version of its full name, netCDF stands for Network Common Data Form. Initially developed in the early half of 1988 by the National Center for Atmospheric Research, it was modeled in the beginning after NASA's CDF (Common Data Format)[18][16]. Originally very close to its conceptual roots, netCDF at first mostly provided an additional level of machine independence to CDF which was limited at the time to VAX/VMS environments. Since then, however, both projects have continued to grow and mature and while still quite similar, now possess many distinguishing characteristics. NetCDF has gone through many revisions and versions since that first release, upgrading to netCDF version 2.0 in October of 1991, with version 3.0 following shortly in June of 1997. The version used for this project is netCDF version 4.0, released June of 2008.

Throughout all of that time, netCDF has remained a cross language, freely distributed, machine independent set of tools and libraries that, along with the netCDF format itself, allow for the creation, access, and sharing of scientific data. Implementations of netCDF can be found in C, FORTRAN, C++, Java, Python, and many other languages. NetCDF is utilized at numerous government and commercial ventures, not only throughout the United States of America, but throughout the world itself.

All netCDF data should conform to six principals for netCDF data, possessing the qualities of self-description, portability, scalability, appendability, sharability, and archivability. That is, netCDF data should include details as to what information it contains and be accessible by computers with disparate methods for storing integers, characters, and floating points. It should efficiently allow access to small subsets of its data and be accepting of the addition of new data without needing to copy the dataset or redefine its structure. Finally, netCDF data should be able to support one writer and multiple readers concurrently and always retain backwards compatibility with previous versions of netCDF.

At its heart, netCDF is an interface to a library of data access functions designed to store data in the form of arrays, n-dimensional rectangular structures containing items all with the same data type. A header stands at the beginning of every netCDF file, containing information regarding the names, types, and characteristics of the dimensions, attributes, and variables found within the file. This dense structure serves to help keep netCDF files compact, however if any changes to the file are later made that must be reflected in the header the entire file may need to be moved to account for the larger (or smaller) header. Thus common netCDF practices recommend that all of the dimensions, attributes, and variables be created before any actual data is written to hopefully avoid a necessitated painful movement of data. Following the header is the data portion of the netCDF file, consisting of a mixture of fixed and variable size pieces corresponding to variables possessing no unlimited length dimensions and variables possessing unlimited length dimensions, respectively. The header possesses offsets from the start of the data portion to each of the variables, to enable rapid retrieval of their constituent values.

A netCDF dimension is used as a building block for netCDF variables. In netCDF dimensions have both a name and a length. The length of a dimension is either an arbitrary positive integer or unlimited (earlier versions of netCDF were limited to only one unlimited dimension per document, netCDF 4 allows for any number of unlimited length dimensions). An unlimited length dimension can continue to grow to any length without limit and could be analogized to the record ID field in conventional record oriented file systems. Dimensions can represent a real physical dimension such as time or height or they can describe more abstract qualities like a sensor's identification number. A basic example of the use of netCDF dimensions would be four dimensions, latitude, longitude, height, and time. The first three dimensions (latitude, longitude, and height) would possess lengths describing the limits of the physical area from which data has been gathered. If data was gathered at three separate heights, for example, the length of the height dimension would be three. The time dimension would possess an unlimited length, indicating that data could continuously be added to whatever variable is constructed using the time dimension as the values being observed changed over time.

A variable is the basic unit of named data in a netCDF dataset and they store the bulk of the data found in netCDF datasets. Variables represent arrays of values of the same type with scalar values treated as zero dimension arrays. Each variable possesses a name, data type, and shape as described by the dimensions specified at the variables creation. A variable can also possess any number of attributes which may be added, removed, or changed even after a variable has been created. Common convention suggests a unidimensional variable be created for each of the dimensions within a netCDF file. These coordinate variables hold information pertaining to the actual values found along a dimensions axis; utilizing our example from before, a time coordinate variable would hold the actual time values along which each data sample was gathered while the height coordinate variable would contain the three heights from which data readings were taken. A demonstration of a non-coordinate variable could be any of the taken data readings, varying over the four dimensions depending on both where and when each specific reading was taken, as long as the data type for all of the values is the same.

An attribute contains metadata, generally about a specific variable. Some attributes instead contain global pieces of metadata, information that describes the entire file itself. Attributes also possess both lengths and data types, although they are far more versatile than the dimensions and variables. Attributes can be deleted or altered in data type, length, or value after creation, properties not shared by either dimensions or variables. Also attributes can be created and added long after a netCDF dataset is first defined, although this poses the same risk as altering the header after creation in some cases; the entire file may need to be moved to account for any additional attributes added post definition. Looking back to our example, each of the five variables, four coordinate and one non-coordinate, would possess a unit's attribute that describes the physical property which the numeric integer values represent. Other possible examples would be attributes describing the maximum or minimum allowable values within a variable, or an offset that applies to all of the values contained by the variable.

In order to comply with the netCDF principal of scalability it is possible to retrieve small subsets of data from netCDF files without having to read through the data that physically precedes it. Using the offsets included in the header it is possible to retrieve individual values from inside any of the variables within the netCDF file utilizing an index number for where along the variable's dimensions the desired value lies. There are further methods designed to provide for accessing larger chunks of a variable or even automatically producing a subsample of a variable's contents. Of note is that in all cases, access to the netCDF data is defined utilizing the concept of the dimensions over which the variables are defined. Returning once more to our example, if the latitude, longitude, height, and time of the measurement you desire are known to you, netCDF already features built in functions that will provide you easy and efficient access to this information. Instead, however, if you wish to know the latitude, longitude, height, and time when the measurement taken was a particular value or fell within the particular range then you would be forced to read through the entire variable in question comparing each value found by hand to your value or range of interest. For a file of large size this procedure can take an unreasonable amount of time creating a need for a better solution.

1.2.2 What is Bitmap Indexing?

Bitmap Indexing, a specialized form of data indexing, has its roots within a paper published in 1985, "Bit Transposed Files", by H. K. T. Wong, H. Liu, F. Olken, D. Rotem, Linda Wong. Establishing two of bitmap indexing's distinguishing features, the paper proposed both the storage of the index's information utilizing bit vectors and the corresponding use of bitwise logical operations to answer queries[5]. Proposed as a possible solution to the inherent difficulty in creating a data index on scientific or statistical data this idea was seen again two years later in 1987 inside a paper titled "Model 204 Architecture and Performance" by P. O'Neil which presented a full description of the first commercial implementation of bitmap indexing[3].

After these initial developments, however, bitmap indexing came to be seen mostly as a useful tool for the creation of low space and high efficiency indexes when dealing with low cardinality data, data with a very small set of possible distinct values. A classic example of this type of data is gender in the context of exceptionally large databases containing information on large numbers of people. While the number of records could be quite high only one of two values would ever be needed meaning two bit arrays, one representing males and one representing females, could contain a data representation of the entirety of the gender dataset. Because of the low computational needs for bitwise logical operations, queries asked utilizing this arrangement are able to be answered in an extremely efficient manner. This view developed in response to the recognition of bitmap indexing's "Curse of Cardinality". Since basic bitmap indexing creates one bitmap for every distinct value found within the data the number of bitmaps, and thus the size of the entire bitmap index, can grow to a very large number in the event that the data possesses high cardinality. As the total size of the bitmap index increases the query time suffers as larger and larger amounts of data are needed to be scanned before any query can be answered. It does not require an extraordinarily high level of cardinality before bitmap indexing becomes a sub par choice of indexing methods creating both larger indexes and providing slower responses to queries.

Another limitation found to be problematic when utilizing bitmap indexing involves bitmap indexing's difficulty with dynamic data. Because each distinct value is represented as a bitmap, adding another record requires increasing the length of the bitmap for every distinct value by one to represent the new record in the case that the new record's value was already present. In the case that a new record's value was not present, a new bit array representing the entire value requires construction. The updating, and to a lesser extent the deletion, of records faces similar performance costs. Oracle, the producer of the highly popular eponymous database, introduced bitmap indexes into their product in 1997 with version 7.3.4. The limitations mentioned above featured largely within their advice to their customers, however, suggesting bitmap indexing be used only in certain limited circumstances, namely when the data was of low cardinality and dynamism and even then only if other columns within the data possessed the same qualities so that they could be joined together using efficient bitwise logical operations.

While bitmap indexing's difficulty in handling dynamic data still proves problematic today, the scientific data addressed within this paper is mostly static in nature as described previously. Thus the "Curse of Cardinality" is by far a more serious problem in utilizing bitmap indexing solutions with the intended data. Three different strategies are utilized to minimize this particular inherent weakness within bitmap indexing. The first strategy, compression, is a relatively simple concept that is likely familiar to many computer scientists. Bitmaps are a highly compressible type of data and can be compressed down to small sizes even using simple compression routines. Indeed, by utilizing very simple compression routines such as run-length encoding the size of bitmap indexes can be compressed smaller than many other indexing options. Even in the worst case for bitmap indexing, a set of wholly unique data points, a properly compressed bitmap index will often be roughly the size of an equivalent B-Tree[11]. The small size of compressed bitmap indexes lowers both the space needed to store them and also the amount of processing needed to access them from disk. For some compression algorithms the resulting compressed bitmaps do not even require decompression before they can answer queries allowing for their direct utilization in logical operations while still in their compressed form.[2]

Encoding is another regularly acknowledged strategy for increasing the performance of bitmap indexes. Instead of creating one bitmap index for each distinct value of the indexed attribute, an encoding scheme is used to reduce the number of bitmaps needed to hold the entire index. An easy to understand example would be binary encoding where instead of creating X bit arrays for the X distinct values of the indexed attribute, $\log_2(X)$ bit arrays are created instead and the binary value of all of a row's bits read together indicates the enumerated value it holds. Thus if an attribute had ten distinct values four bitmaps could be employed using binary encoding to describe the value held by each data point. The downside of this approach, however, is the need to read all four bitmaps to properly answer queries which could be solved by reading only one bitmap using the more general basic bitmap encoding. For example, if a query simply requested all data points that possessed a given value the basic bitmap encoding could examine the single bit array representing that value and answer the query completely, whereas an index utilizing binary encoding would need to examine all of the bitmaps in order to determine which points possessed the requested value and which did not.[5] Thus, different encodings generally represent compromises between the space required to actually store the bitmap indexes and the speed in which they can answer queries. This idea obscures an even more general principle regarding different encoding schemes, however. What the various bitmap indexing encoding schemes truly allow is for the bitmap index's creator to customize the bitmap index for the types of queries it will predominantly be asked. Different encoding schemes exist for optimizing a bitmap index to answer equality or range queries, for example, and knowledge of the type of queries a given bitmap index will predominantly be asked allows for the choice of an encoding that will best serve those queries.[1]

The third strategy utilized is the concept of binning. A seemingly simple strategy, binning merely suggests a bitmap index creator dealing with a high cardinality attribute utilize each bitmap not as an individual value, but as a range of values. In this way, a binned bitmap index can quickly and efficiently exclude those data points that lie within bins that are certainly not within the requested set by comparing the range the bin encodes for against the requested values. If no requested value falls within the range of the bin no data point within the bin should be returned. Likewise, those data points which most certainly are within the requested set can also be swiftly selected by returning all data points within a bin whose range is completely contained within the requested values. Any bins left over constitute edge bins, whose set of values within the bit overlaps, but does not equal or contain, the set of requested values. For example, if a bitmap index was created with five bins possessing the values of [1 - 10], [11 - 20], [21 - 30], [31 - 40], and [41 - 50] and a query is submitted asking for those data points whose values are less than 35 but greater than 7, then the last bin, [41 - 50], can be instantly eliminated. Bins [11 - 20] and [21 - 30] can be instantly returned, as every data point within them falls inside of the desired range of values. Bins [1 - 10] and [31 - 40] would constitute the edge bins in this case and would now need a candidate check, an examination of each data point individually to determine which ones fall inside of the desired value and which do not. Just as there are many compression and encoding strategies, so to are there many approaches to binning. The most basic binning approach merely consists of equal width bins that evenly divide up the range of values for the indexed attribute. This simple approach, however, ignores the reality of most real world data and often results in misshapen bins due to naturally occurring clusters of values within the indexed attribute's range. More advanced approaches take the nature of the indexed data into account and attempt to produce equally weighted bins throughout the data or instead consider the work intended for the index and purposefully position bins to ensure likely edge bins are smaller than the remainder of the index. One particularly powerful binning strategy goes so far as to propose an additional data structure used to increase the candidate check's efficiency. Candidate checks are normally the bottleneck within a binned bitmap index, often due to having to randomly access all of the data points within a bin and check them individually. Order-preserving Bin-based Clustering, however, proposes the use of clusters of the data points within each bin stored together so that any needed candidate check within a multi-valued bin will proceed at a much faster pace than usual[12]. Using order-preserving bin-based clustering does cost additional space above the space needed for more traditional binning, trading away some of the spatial savings realized by utilizing the binning strategy for an increase in query response times. While deciding on how many bins to use remains a difficult problem to resolve utilizing order-preserving bin-based clustering has been shown to break the "Curse of Cardinality" for bitmap indexes.

1.2.3 What is FastBit?

FastBit[13][9], developed by the Scientific Data management group at the Lawrence Berkeley National Laboratory, is an open source free bitmap indexing toolkit. FastBit is highly developed and utilizes many advanced bitmap indexing algorithms not only for querying of the indexed data itself but also for efficiently and optimally compressing, encoding, and binning the bitmaps generated. Intended for use with complex high cardinality static scientific datasets, FastBit was introduced in 2007. Since then it has continued to be refined and expanded upon and is currently in use within many applications which deal with complex high dimensional scientific data.

For compression purposes FastBit utilizes an award winning patented bitmap indexing compression algorithm known as WAH, or Word Aligned Hybrid. Compression routines seek to lower the I/O costs of loading the on-disk bitmap indexes into memory for processing, decreasing their size and allowing them to load faster. For many compressed bitmap indexes, however, the majority of the time utilized to answer queries was spent within the CPU performing logical operations. Based on this realization WAH compression was designed to optimize its usage within the CPU by aligning its compressed bitmap indexes along word boundaries. In WAH compression, the first bit of every word is used to distinguish the word as either a literal word or a fill word. For literal words, the remaining thirty-one bits (assuming thirty-two bit words) contains the uncompressed data from the bitmap indexes. Fill words on the other hand contain a fill bit which indicates what repeating value the fill word is compressing followed by a count of the number of literal words worth (thirty-one bits, again assuming thirty-two bit words) of fill bits the fill word represents. In analysis this approach has been proven optimal[7] as the query response time is proportional to the number of hits generated by the query while the compression rate achieved still leaves the compressed bitmaps smaller than a comparable B-Tree. In those rare cases where a user wishes to leave some or all of their bitmap indexes uncompressed FastBit also allows for the storage of uncompressed bitmaps based either on their density or compression ratio.

By default FastBit does not employ any encoding techniques within its bitmap indexes, instead simply utilizing the basic bitmap index equality encoding scheme consisting of one bitmap per indexed value. FastBit possesses the ability to use two other types of encoding, however, range and interval encoding. Range encoding utilizes the same number of bitmaps as the standard equality encoding but is optimized for queries requesting a range of values. Interval encoding on the other hand decreases the number of created bitmaps. As discussed earlier this decreases the storage space required to hold the index but increases the time needed to query it as more bitmaps need to be checked to produce a query's answer.

For binning FastBit offers the same level of flexibility presented with encoding. A user can choose to create any given number of bins of almost equal weight or at designated boundary lines. To designate bin boundaries a desired precision or formula can be given or a direct list of boundaries to utilize. FastBit even allows for the use of order-preserving bin-based clustering as discussed earlier, creating a set of files containing the reordered values and storing them with the generated bitmap indexes.

In order to load data within FastBit a user can simply identify a file of comma separated values along with any options they wish to utilize in the indexes construction through a command-line interface and FastBit will generate the indexes automatically. FastBit's command-line interface also allows for the querying of the generated bitmaps using a subset of the SQL syntax. This allows queries to be written in the same format used in many other database applications and thus provides an easy to use interface which the majority of users will already be familiar with. The output produced via FastBit can be written to a file as a set of comma separated values or simply output to the screen. Overall FastBit presents an efficient implementation of bitmap indexing algorithms, allowing for the indexing and querying of high dimensional static scientific data.

1.2.4 What is ncks?

Ncks, short for netCDF Kitchen Sink, is a tool included within the open source nco suite of operators. Released as an open source project in March of 2000 nco, or the netCDF Operators, was begun by Charlie Zender, an Associate Professor of the University of California. Seeing a need for tools and applications designed for the analysis, manipulation, and transformation of netCDF documents, the nco project contains several different applications that offer a large degree of functionality to base netCDF files.[15]

As suggested by the name “Kitchen Sink”, the ncks tool itself contains a number of disparate functions primarily aimed at converting netCDF documents into different formats, predominantly either ASCII text or flat binary. While such functionality is simple in concept, in implementation it is far different with the difficulty arising largely due to netCDF document’s inherent complexity.

Within ncks a user is provided with options for the retrieval of all variables specified, all variables not specified, or simply all variables in the dataset. Further options allow for the extraction of any associated coordinate variables along with numerous choices regarding the formatting of the output. The name and index location for each variable can be provided along with the value at that data point, or instead output can simply consist of a labelless collection of values. Metadata can be preserved if desired, or the values within any unit attributes can be included within the output. Obviously the transformed output produced through ncks lacks the highly compressed data format found in netCDF. As such, any meaningful extraction of data using ncks will result in an ever larger file, although the precise increase in space will vary depending on the specific manner of extraction specified.

Chapter 2: Proposed Architecture

2.1 System Overview

Often, the first step in the design of a complex system is the construction of a detailed schema to help visualize the actions taken by the system when in use. For the use of bitmap indexes with high dimensional scientific data stored in netCDF files the architecture as depicted in Figure 1 is proposed.

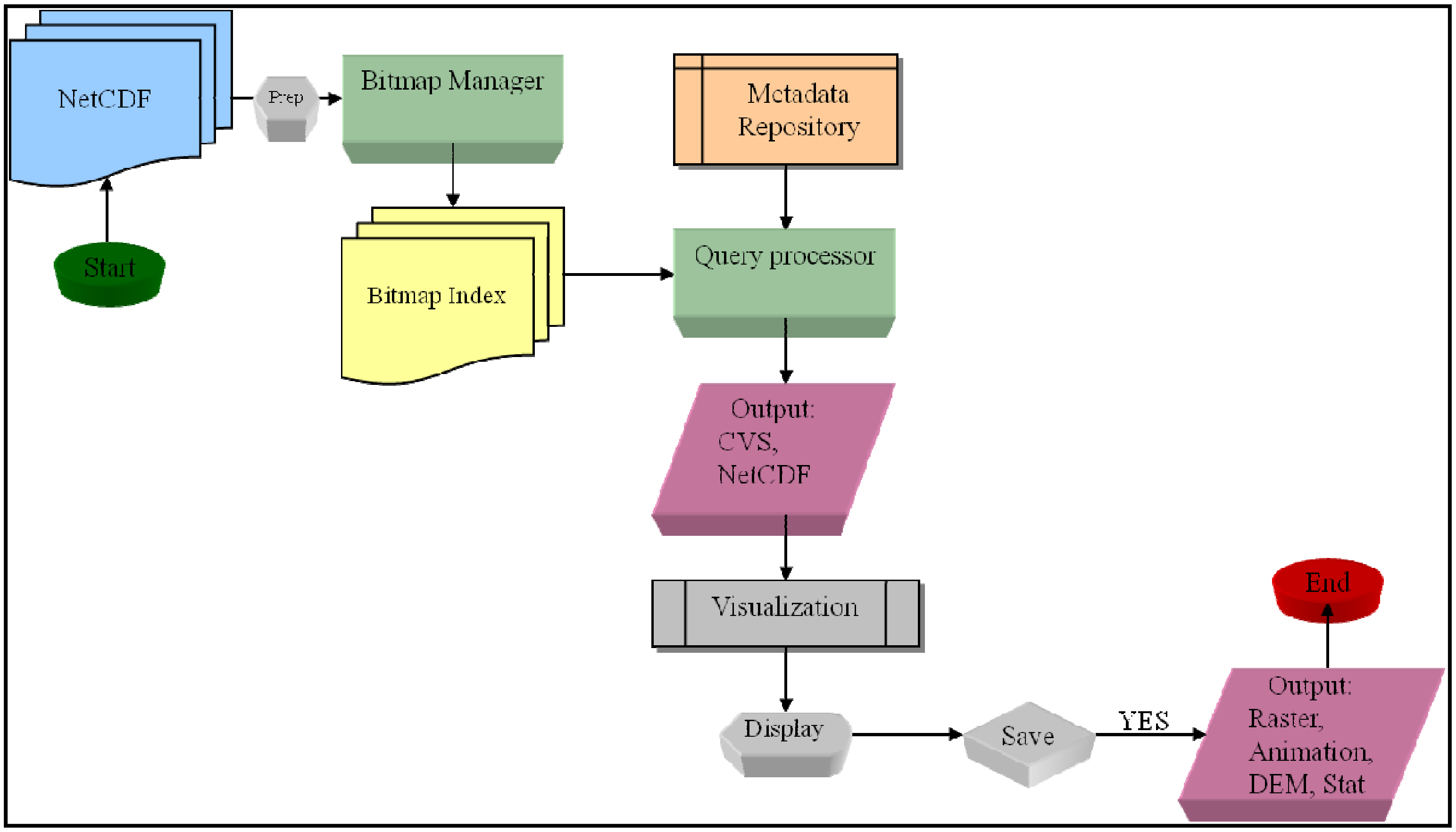


Figure 1: System Flowchart

A *Bitmap Index Manager* is proposed to build and maintain a bitmap indexes themselves. The *Bitmap Index Manager* is expected to provide for single file and multiple file bitmap indexing for netCDF scientific data. Further, the netCDF files may be accessed either locally or across a network. The *Metadata Repository* will hold any relevant metadata found within the netCDF file's header. This metadata will aid in maintaining organization when several bitmap indexes are used, as well as providing a boost to query speed by screening out queries from which no point (or perhaps all points) meets the desired criteria. Further, the metadata will be utilized in any visualization of a query's results by providing details such as the extent of the measured area. The *Query Processor*'s role is to transform the user submitted high level queries into sequences of bitwise logical operations executed in the reduced search space generated using the *Metadata Repository*. This architecture allows for the recognition and retrieval of the specific records desired by the user. Compared to reading through the entire file, this design should result in a substantial speed up.

The *Query Manager* will seek to optimize the processing of a number of primitive operations which form the basis of high level queries. Recent studies[6] on the query processing of mesh data (such as data stored in netCDF files) identify four classes of primitive operations:

Temporal Operations: query a mesh during a time interval or time point.

Spatial Operations: locate a mesh region of interest

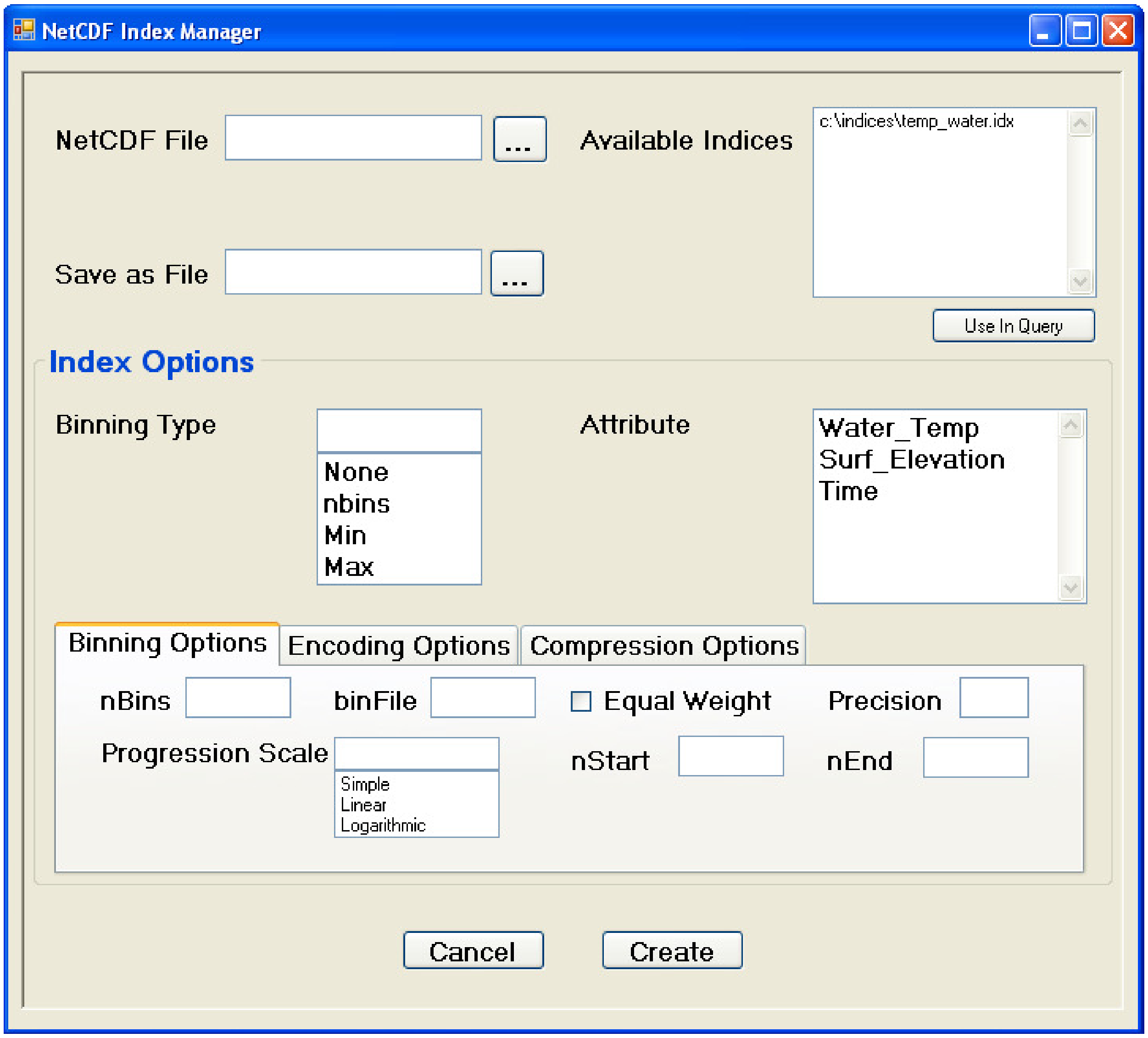
Similarity/Proximity Operations: determine region(s) that are similar to a given region using a particular distance metric function. The most common examples are range and k-nearest neighbor searches[8,10].

Statistical Operations: aggregate per group for a given region. The aggregation may involve spatial, temporal or field variables.

The details of how our proposed netCDF enabled FastBit handles each of these classes of operations are presented in chapter 4.

2.2 Proposed GUI

To utilize this proposed architecture a GUI has been designed with the collaboration of Fareed Qaddoura. Figure 2 depicts the Index Manager screen of this GUI. A user can either browse to a specific netCDF file or enter a URL identifying one. Any preexistent bitmap indexes having already been created for the netCDF file will be displayed and can be selected and used with a query right away via the “Use In Query” button. If no bitmap indexes already exist for this file, or if none of the indexes available are appropriate for the desired query, a new index can instead be created using the many index options provided through the “Index Options” section occupying the bottom half of the screen. As can be seen in Figures 2, 3, and 4, all of the various bitmap index creation options exposed through FastBit are allowed. When choosing to create a new index, the variables to be indexed can be selected from the attributes list.



c:\indices\temp_water.idx

Binning Type: None, nbins, Min, Max

Attribute: Water_Temp, Surf_Elevation, Time

Progression Scale: Simple, Linear, Logarithmic

Figure 2: The Index Manager and Binning Options Tab

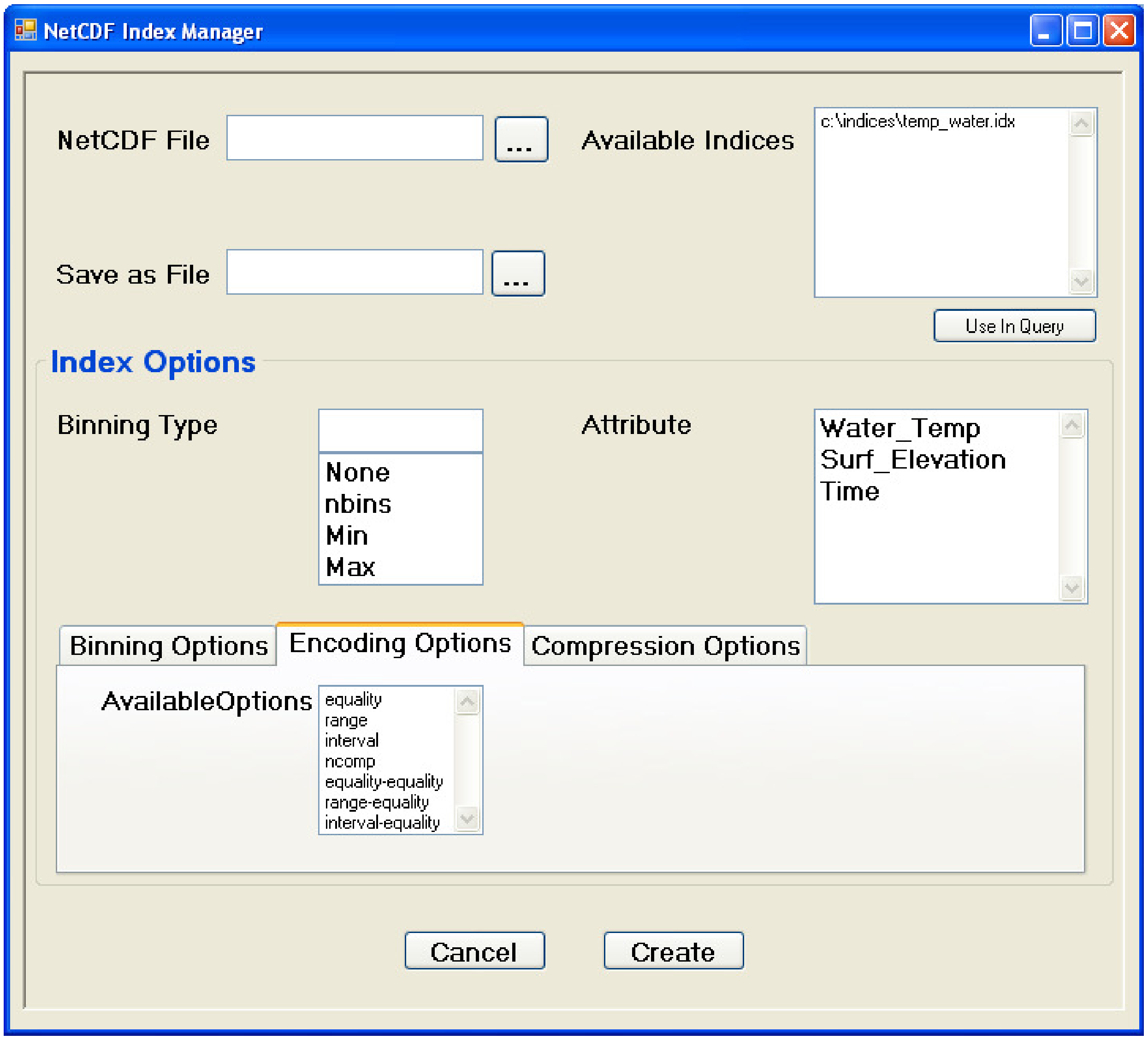


Figure 3: The Encoding Options Tab

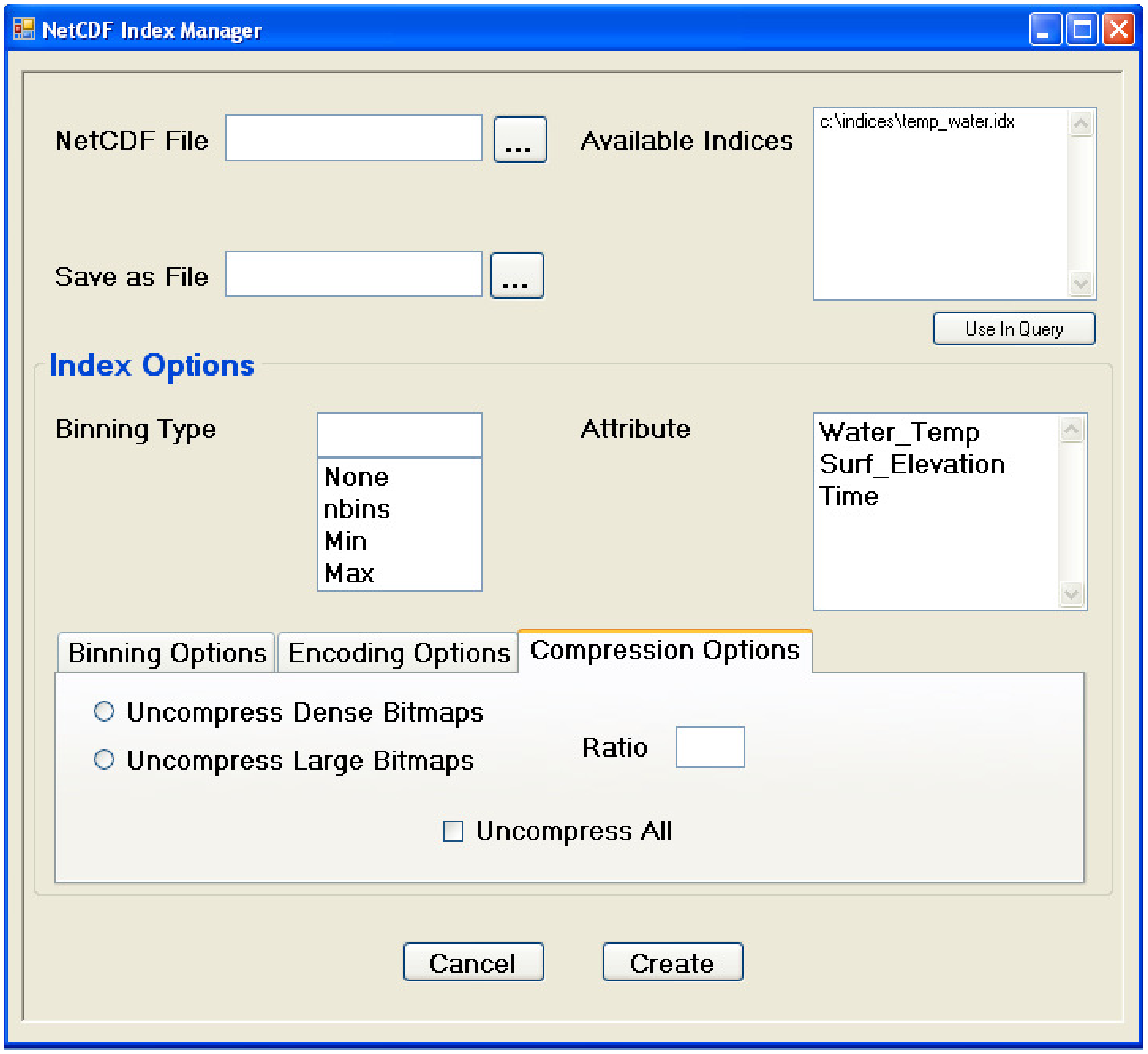
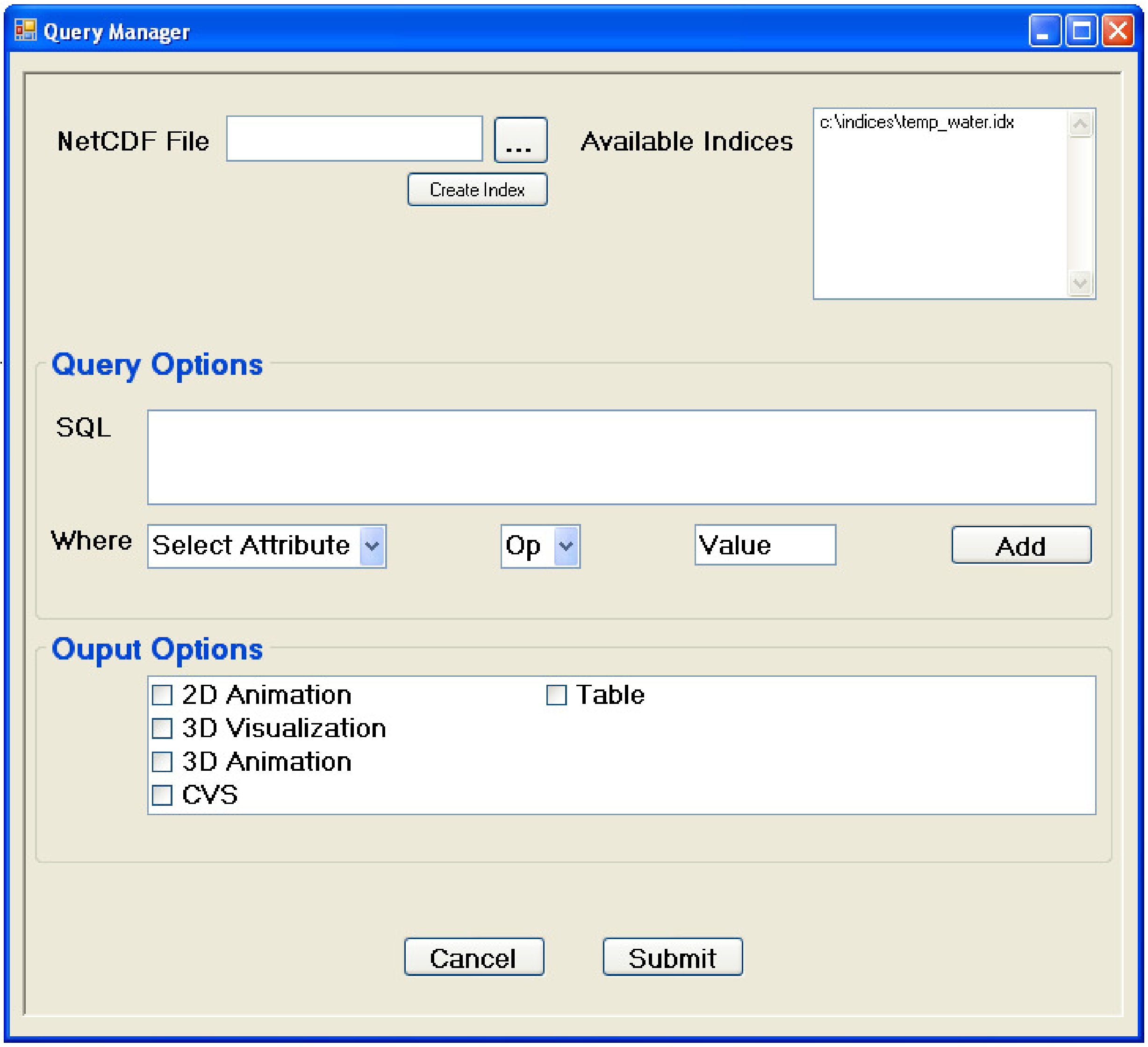


Figure 4: The Compression Options Tab

Once an appropriate bitmap index is either selected or created, the Query Manager screen of the GUI can be used to submit a desired query by the user either by typing the query directly into the SQL box or by using the drop down Where boxes to create and add Where clauses, as seen in Figure 5. Further, a number of different output formats are offered through the Query Manager screen with options ranging from pure comma separated value text results to 3D animations of the resulting data.

This arrangement leverages FastBit's many abilities within the proposed architecture to minimize the learning curve for any new users. Further, the user interface allows a user to easily see all of the possible options within the proposed architecture, possibly exposing capabilities the user did not realize were available.



Available Indices: c:\indices\temp_water.idx

Figure 5: The Query Manager Screen

Chapter 3: FastBit Indexing and netCDF Integration

3.1 Method Used

As mentioned previously, by default FastBit is only able to interpret one type of input, a file of comma separated values. While the comma separated value reader utilized by FastBit is tolerant of irregularities within the data, there is no capacity for interpreting anything similar to netCDF data. In order to load the data stored within a netCDF file into FastBit, one would need to first convert the data into comma separated value format. Luckily, several utilities are already existent for the conversion of netCDF data to comma separated value format, one of which, ncdump, comes packaged with netCDF itself. However, the concept of comma separated values is only loosely defined, and while ncdump and FastBit both utilize comma separated values in name, in reality the output produced via ncdump proved unreadable by FastBit.

Another tool set offering netCDF to comma separated value conversions was located in nco, the NetCDF Operators, a set of standalone command line processes aimed towards various manipulations of netCDF files. One of the tools, ncks or NetCDF Kitchen Sink, allowed for a netCDF to comma separated value format operation that more closely hued to FastBit's expected output. With the correct configuration of ncks's many options, in fact, FastBit ready comma separated value proved achievable, and were able to be loaded directly into FastBit. Using this tool, a 1.4 GB netCDF file (the largest locatable for the duration of this project) was converted to a comma separated value file in roughly 25 minutes, enlarging to 6.2 GB in size due to the large difference in the compactness of the stored data inherent in the netCDF and comma separated value formats. This set of comma separated values was then loaded into FastBit to create a 6.8 GB bitmap index in 7 minutes, using the default settings employed by FastBit when loading data.

The comma separated value file produced via the process detailed above is strictly temporary in nature; once the FastBit bitmap index has been generated, there is no further need to retain a copy unless further indexes are intended in the future. Still, when dealing with excessively large netCDF files, it is possible that the storage space cost required to hold both the comma separated value file as well as the bitmap indexes may be prohibitive. As such, an attempt to even further integrate FastBit and netCDF was undertaken. As both the nco tool set and FastBit are open-source projects, the source for each was freely obtainable and modifiable. The first step towards integration of the two tools was the trimming and removal of all of ncks's functionality, excepting the ability to read a netCDF formatted file and produce a comma separated value version of the data, suitable for FastBit consumption. After this, the initial plan was to then move the remaining code into FastBit itself, adding the functionality directly into FastBit's data loading processes so that netCDF files could be read as simply as comma separated value files. Even after removing all extraneous capability, however, the ncks tool still proved to be rather large; too large, in fact, to be a good candidate for the kind of transplanting originally proposed.

Instead the trimmed ncks tool was modified to send its output to a Unix socket while FastBit's data loading tool was altered to listen to that socket when expecting netCDF input. In this manner, the data was seamlessly converted out of the netCDF file format and loaded into a FastBit bitmap index with no need to create a file to hold the converted comma separated values in the middle. Because the tools remained two separate distinct processes, however, a shell script was created to call both of them at the same time, to give a unified user interface to using both of the newly created tools.

3.2 Results Obtained

Using the ncks utility in the nco package, speedup results were obtained demonstrating the advantage in efficiency afforded utilizing the netCDF enabled FastBit bitmap indexes. With the largest netCDF file obtainable, 1.4 GBs, a CSV export measuring 6.2 GBs was produced in 25 minutes. This file was then processed using FastBit, resulting in a 6.8 GB bitmap index after only 7 minutes of work.

The file used measured temperature over four dimensions, three spatial (latitude and longitude, as well as depth) and one of time. Simply searching through the entire netCDF file for a desired temperature required 20 minutes of time and absent FastBit this would be the only method for performing any kind of selective search. Using this created bitmap index, however, times were greatly faster. A simple equality search for a specified temperature returned in only 1 second, twelve hundred times faster than before. A bounding box query requesting all temperatures inside of the specified values at the given depth returned in 4 seconds, a three hundred time speedup. Even a range query, requesting all temperatures above a given threshold produced an answer in only 4 minutes, still five times faster than previously possible. See table 1 for some example queries and the time needed to complete them, as well as the amount of speedup demonstrated versus a complete file scan.

Query	Equality on Temp	All Temp for Timeslice	Bounding Box	Range on Temp
Runtime	1 second	4 seconds	42 seconds	4 minutes
Speedup	1200x	300x	20x	5x

Table 1: Sample Queries and their Respective Runtime and Speedups

As can be seen above, for a nominal amount of creation time, a bitmap index of a netCDF file can be created allowing for an otherwise unobtainable level of interactive access to the data contained within. This access further makes it possible to perform even more complex operations upon the dataset, such as the similarity searches discussed in the next chapter.

Chapter 4: Implementation and Viewing of Spatio-Temporal Queries

Recent studies[6] on the query processing of mesh data (such as data stored in netCDF files) identify four classes of primitive operations, temporal, spatial, proximity, and statistical. Implementations for each of these classes within the integrated netCDF-FastBit framework established in chapter 3 are discussed below. Further, the process of visualizing the resulting output from the submitted queries is discussed, along with some example visualizations.

4.1 Temporal Operations

As their name suggests, Temporal Operations are operations intended to function along the dimension of time. Three simple examples of this would be the concepts of before, after, and during.

NetCDF does not utilize any built in date data type; however, as the data involved is very often of a geospatial-temporal nature some measure of time is needed. Generally this is achieved utilizing the standard measure of UNIX time[17] (the number of seconds since January 1st, 1970) or some variant thereof. This means temporal operations can be generalized down to simple arithmetic problems between two integers. In order to search for events or measurements before a certain time, one would only have to convert the desired date into its corresponding integer and submit a search specifying interest only in time values less than the provided value. Likewise, it is simple to search a span of time by indicating an interest only in results that fall between two specified time values. As these operations can be performed using simple equality comparisons FastBit can efficiently select out only those data points falling within the time of interest.

As an example, to only return results from a specific time slice, the clause
time = X could be appended in the Where statement, ensuring that any values returned would have been observed at the given point in time. To construct a query specifying a time before or after the given time the equals sign would simply need to be replaced using a less than or greater than signs. A span of time could be indicated using **X < time < Y,** which would indicate returned values should have been measured between the two points in time specified.

4.2 Spatial Operations

Spatial Operations offer up a close analogue to the Temporal Operations mentioned in the last section, except they apply to the three special dimensions. A common concept within spatial operations is a bounding box, a set of four coordinates which form a box that is then useful within the context of spatial operations. Several relations can be defined using a bounding box, such as contained by, disjoint, or overlapping.

As our netCDF files of interest contain data relating to meteorological conditions upon the globe of the Earth, latitude and longitude measurements provide convenient methods for defining a spatial location on the globe from which a data measurement or reading was observed. Similarly, for data taken not only along different longitude, latitude points, but also at different altitudes (or depths, for those measurements performed under the sea, or perhaps even under ground) simple integer variables can easily store a numerical depiction of the location. Just as with the temporal operations, it is easy for FastBit to construct simple equality comparisons between any of these dimensions, in any possible configuration. While FastBit does not implement any standard spatial search features, such as a bounding box search, they are very easily to replicate using two-sided inequalities.

A bounding box search for all points with a box that stretched from longitude, latitude points (0, 0) to (20, 20) could be expressed within FastBit as

0 <= latitude <= 20 and 0 <= longitude <= 20.

A three dimensional element could be easily introduced, either to create a "bounding cube" instead, or to specify a single level of elevation within which to perform the bounding box search. For other spatial shapes a list of OR'd longitude, latitude points would be used to describe the path and shape traversed by the shape. By simply reversing the above query for points within the bounding box from (0, 0) to (20, 20) we can create

(0 >= latitude or latitude >= 20) and (0 >= longitude or longitude >= 20)

which will return all points outside of the bounding box specified.

4.3 Proximity Operations

While the last two classes of operations dealt mainly with locating points whose coordinates shared a specified relationship with another given set of coordinates, Proximity Operations represent a more complicated problem. Instead of looking for direct relationships between two sets of coordinates Proximity Operations perform comparisons between a data points coordinates, returning values close to the specified point utilizing a given metric, in this case physical distance.

As seen from the previous two sections, FastBit's subset of SQL easily and efficiently handles queries involving equalities. What is more problematic is when instead of having a specific set of longitude, latitude points, the user possesses a single longitude, latitude point and a measurement of distance around which they are interested. Determining which points fall within this specified range is complicated, not only because longitude and latitude do not directly correspond to any commonly used measurement of distance, but also because, due to the curved nature of Earth's surface, calculating the range between them is not a matter of simple addition or subtraction (as it would be if longitude, latitude points represented points on a grid rather than points upon a sphere). Similar problems appear frequently in many fields, particularly those related to navigation, where knowledge of what objects lie within a specified distance provides an obvious utility.

To solve this problem we introduce the trigonometric haversine function[14],

haversine(d/R) = haversine(Δlatitude) +

cos(latitude1)cos(latitude2)haversine(Δlongitude),

which computes the great-sphere distance (the shortest distance over the surface of a sphere) of two points located on the globe, utilizing the points' longitude, latitude values. In this formula the variable **d** represents the distance between the two points while **R** is the radius of the sphere itself. Since in this case we are interested in **d**, the distance between two longitude, latitude points, we can solve the haversine formula for **d**, which results in

d = 2Rhaversin-1(h) = 2Rsin-1(√h).

This can be expanded further to

d = 2Rsin-1(√(sin2(Δlatitude/2) + cos(latitude1)cos(latitude2)sin2(Δlongitude/2).

Using 3,956 miles as an estimate of Earth's radius we can express the previous expanded formula using built in mathematical functions found within FastBit's SQL implementation, giving us this SQL statement,

2 * 3956 * asin(sqrt(pow(sin((specified latitude - latitude) * 0.0174/2), 2) + cos(specified latitude * 0.0174/2) * cos(latitude * 0.0174/2) * pow(sin((specified longitude - longitude) * 0.0174/2), 2))) as distance.

The specified latitude and longitude mentioned in the formula refer to the longitude, latitude point from which the range is being measured. It is a simple matter to create a shell script that can accept two variables and submit the above SQL statement to FastBit, inserting the provided latitude and longitude where appropriate within the query. The presence of 0.0174 repeatedly throughout the SQL statement is merely to convert the decimal representations of latitude and longitude found within the data itself into radians, by multiplying by an approximation of pi divided by 180. In cases where the longitude and latitude were stored within the netCDF file already in radians, the values should be left off. By using this SQL query within the Select statement, this formula will compare the specified longitude, latitude point against every longitude, latitude point within the dataset and calculate the distance between them, presenting the results in a new column, named distance in this instance. Returning to the original problem at hand, those points within our range of interest can then be easily picked out by an additional clause in the Where statement, **distance <= X**, thus returning the values for those longitude, latitude points that lie no more than the specified distance away from our starting point. Obviously, however, this formula represents a heavy computational load, which must be applied between the given longitude, latitude point and every longitude, latitude point within the dataset.

With even a reasonably sized dataset, this computational cost can rapidly become quite expensive. Therefore, to help limit the number of computations required, a two step filtration process is proposed. First, a rough estimate will be applied that will include every longitude, latitude point within the area of interest as well as several outside. It is estimated[4] that each degree of latitude is roughly equivalent to 69 miles, while each degree of longitude is equivalent to the cosine of the latitude multiplied by 69 miles. Using these estimates we can construct a bounding box that will always possess all longitude, latitude points within the specified distance of the starting point, as depicted in Figure 6, and express it in FastBit acceptable SQL as

(specified latitude - range/69) <=latitude <= (specified latitude + range/69) and (specified longitude - range/cos(specified latitude) * 69) <= longitude <= (specified longitude + range/cos(specified latitude) * 69).

By adding these two clauses into the Where statement of the SQL query, a bounding box is formed that subsets the points within the dataset. This subset of the entire dataset's longitude, latitude points will then be given to the second filter, the haversine function presented above, so that those points further from the specified point than the given distance can be removed from the final results. By applying this two step filter to the Range query devised here, very large speedups are demonstrated within the runtimes of the queries, alleviating the time requirements of using the haversine Range query by itself. This speedup is, as expected, greater the more points it can manage to exclude from the haversine function used to compute the distance. If the area transcribed by the bounding box occupies the majority of the space defined within the file, speedup will be very limited. Table 2 and 3 depict the time needed and speedup obtained using this bounding box filter.

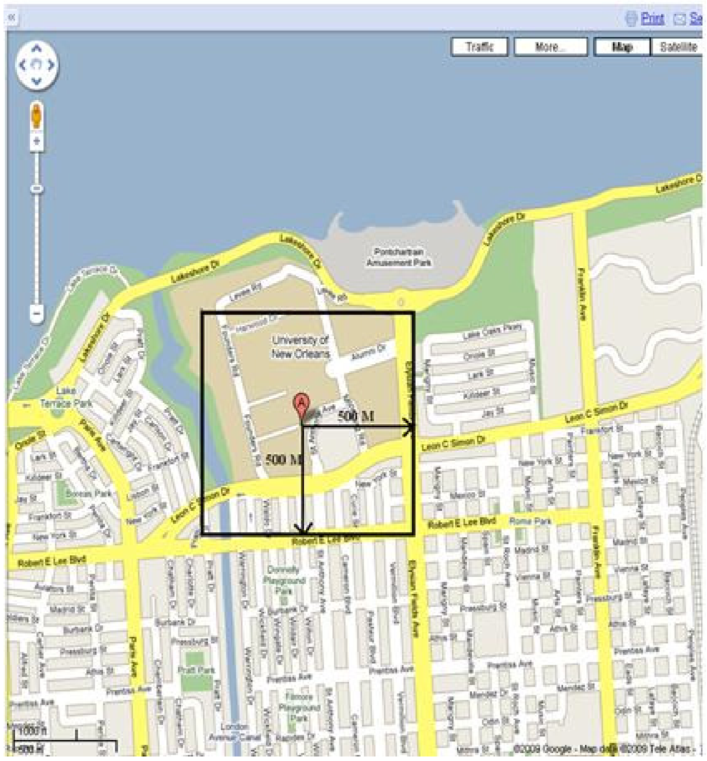


Figure 6: An Example Bounding Box Describing 500 Meters

Distance	5	15	25	35	45
Time w/Bounding Box	0.125s	0.523s	0.604s	0.683s	0.848s
Time w/o Bounding Box	6.132s	6.308s	6.318s	6.570s	6.147s
Speedup	49x	12x	10x	10x	7x

Table 2: Speedup with and without Bounding Box Filter, ~8.75 Million Points

Distance	5	15	25	35	45
Time w/Bounding Box	0.183s	0.588s	0.828s	0.833s	1.234s
Time w/o Bounding Box	146.391s	150.083s	147.361s	154.347s	149.535s
Speedup	1039x	255x	178x	185x	120x

Table 3: Speedup With and Without Bounding Box Filter, ~218.5 Million Points

Having devised a method by which all points within a certain distance of a given point can be returned, we can now extend this Range query further to produce a pseudo-KNN. By sorting the returned results according to ascending distance, and limiting them to the first K results, our returned longitude, latitude points contain only the K nearest points to the starting point. While superficially resembling a KNN search, this operation is identified as a pseudo-KNN query for an important reason. A true KNN search will return the K nearest neighbors, no matter the distance separating them. This search, however, will only return the K nearest neighbors within a given range. It is certainly possible that less than K points will be within the range specified if the range is particularly small, or the dataset does not cover the area of interest evenly.

To enhance the usability of these large complicated SQL statements, an easy to use shell script was created so that a user merely needs to identify the longitude, latitude point of interest, as well as a range around the point to search. While created solely for testing purposes, the script can be extended to easily substitute the haversine formula and bounding box filter into any query requiring either a Range or pseudo-KNN search.

4.4 Statistical Operations

When dealing with large amounts of data, it is often useful to be able to provide some level of statistical analysis relating to the data as a whole. This kind of analysis allows for the understanding of trends within the data, and provides for the ability to not only forecast future changes within the data, but to also explain on a deeper level precisely how the disparate data points interact with one another. By collecting and analyzing various data points, Statistical Operations can offer new ways of presenting and viewing pieces of data, allowing for more accurate interpretations of how and why the data points are changing.

By default, FastBit implements four Statistical Operations within its default SQL subset implementation: Avg, Max, Min, and Sum. Avg provides the mean value over the column it is given. For example, if your data was a set of temperature readings over a period of time, **Avg(temperature)** would provide the average temperature over the entire time span. Max instead gives the maximum value held over the entire column, and extending the previous example, could be utilized to find the highest temperature over the measured time span. Min acts as Max's opposite, and instead finds the minimum value over an entire column. Again, looking back to the previous example, Min could be used to find the lowest temperature during the period of observation. Finally, Sum presents all of the values within the column, summed together. In the context of the example used so far this function has little relevance as providing the summed total of all temperatures over a time period does not relay any useful information. For other calculations, however, Sum can be a useful tool, for example, providing the total amount of rainfall in an area over a period of time. When utilizing any of these Statistical Operations, FastBit performs an implicit SQL Group By clause, utilizing any of the selected variables not appearing within a statistical function. Finally, a column is appended to the results generated utilizing these Statistical Operations with a Count of the number of rows utilized in determining their values.

In addition to this array of Statistical Operations, other complex statistical calculations can be built utilizing these default four operations as basic building blocks. The most frequently appearing value for a data column, the Mode, can be calculated by selecting the column in question as well as its Avg.

The resulting SQL statement will be similar to **select temp, avg(temp) sort by desc count(*)**. FastBit will perform the implicit Group By upon the column and by ordering the resulting column in descending order, the most frequently occurring value may be found. Other Statistical Operations will require changes to FastBit's current parser for SQL queries, or an alternate function which can accept the results of several queries and produce the desired value. Computing the Standard Deviation, for example, would currently be impossible as FastBit could not determine what the differences between a column of values and the average of those values is.

4.5 Visualization

The resulting output from any of the operations discussed above, or for any operation upon FastBit in general, is a set of comma separated values output to either screen or file. For the most part, however, this kind of output is difficult to use, or even understand, without some kind of additional help. To advance towards that goal the process of visualization was suggested.

With the aid of Fareed Qaddoura 2D and 3D visual representations from the test 1.4 GB netCDF file were created using raster layers created for each specified variable in the netCDF file. For animating purposes, a time series raster was created from another specified variable, then applied using ESRI's arcscene[19] animation manager. Figure 7 presents an example of a 2D visualization, while Figure 8 depicts a 3D visualization.

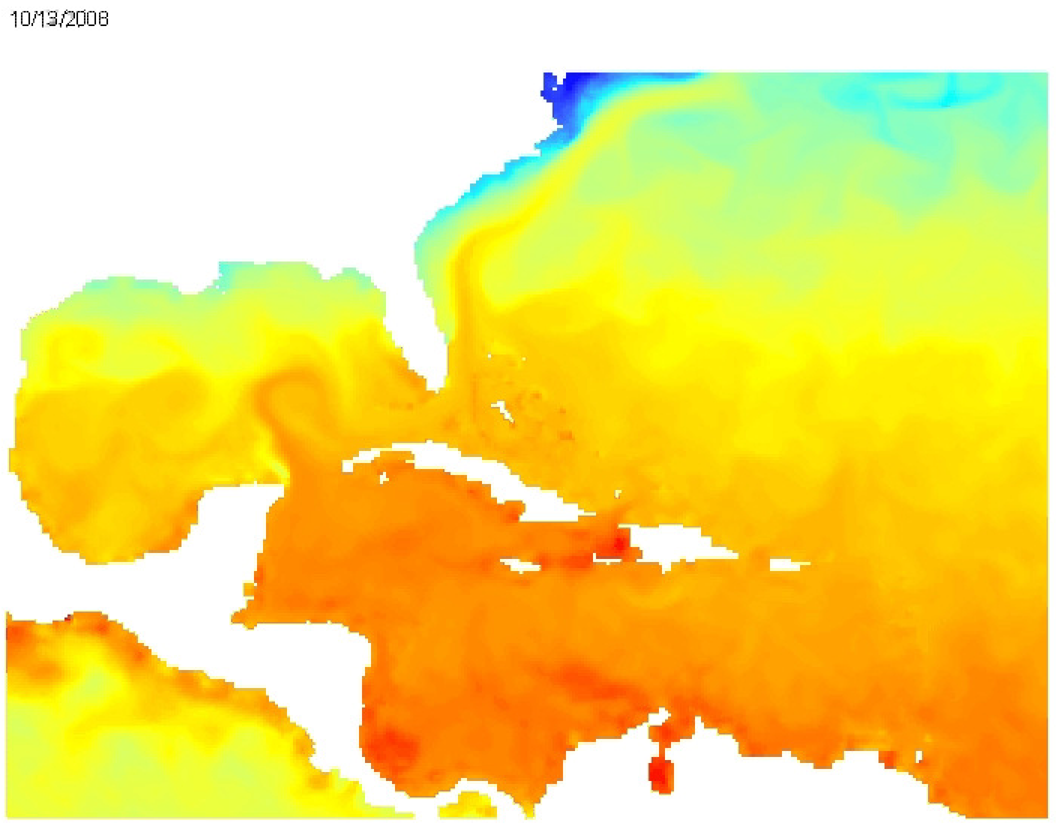


Figure 7: A Still Frame From a 2D Animation of Water Temperature

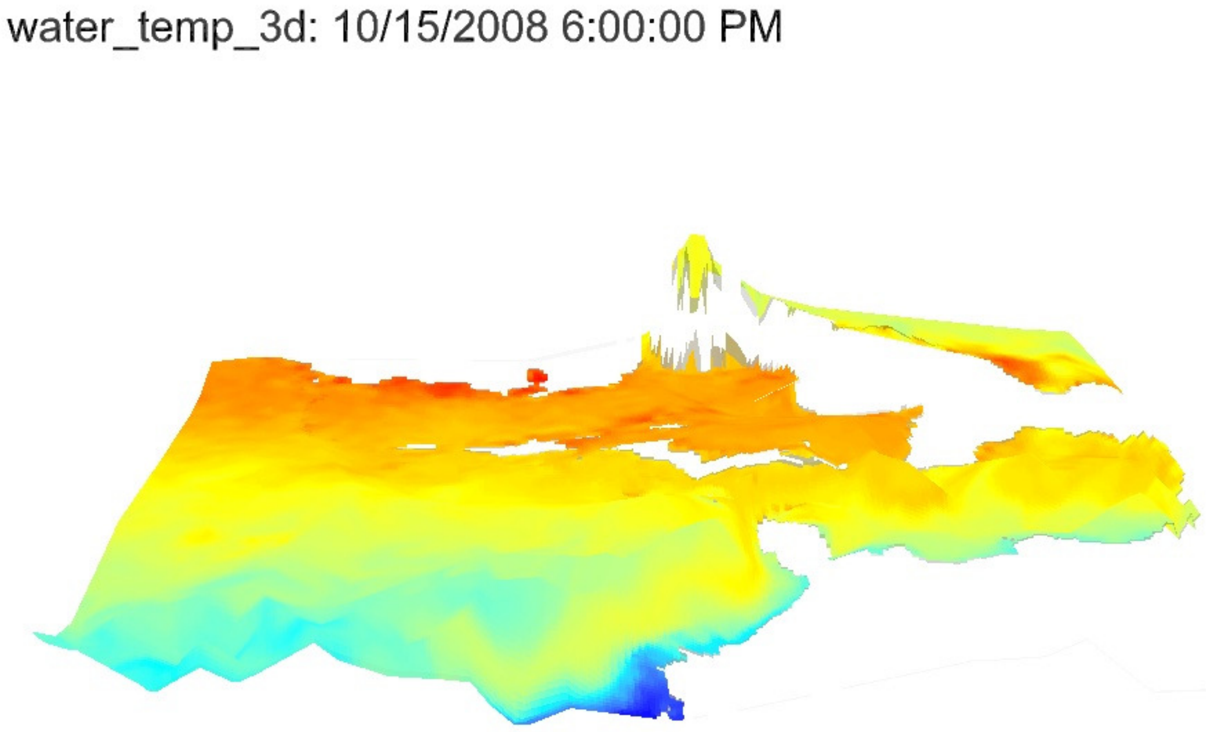


Figure 8: A Still Frame from a 3D Animation of Water Temperature

Chapter 5: Conclusions and Future Work

5.1 Future Work

There remains many different ways in which this project could be expanded even further. Currently the processes discussed throughout this paper have been written externally to the GUI as presented in Chapter 2. A large amount of work could be expended bringing these external processes within the proposed GUI and made native to that interface. Further, the visualization discussed in Chapter 4 must still be created largely by hand, as ESRI's ArcGIS desktop suite cannot directly read netCDF or comma separated files. As such, a user is currently required to interpret both the metadata within the netCDF file as well as the comma separated value results from FastBit for the creation of the visualization step's raster layers. For the purposes of further visualization, a way to incorporate the input comma separated value FastBit output into the visualization process is needed. It is likely scripts could be implemented to create the visuals. Based on the outcome of the previous steps, the proposed GUI's design will need to be updated.

For purposes of netCDF and FastBit integration, a tighter coupling between them should also be possible. The trimmed ncks tool may have room for further cuts, finally allowing it to be wholly contained within FastBit and eliminating the need for shell scripts, sockets, or any other extraneous tools outside of FastBit itself. Alternatively, the ncks tool (the original or trimmed version) could serve as a template for the writing of a new, customized netCDF to comma separated value conversion tool built into FastBit from the beginning. It is possible that by building a tool with the express purpose of utilizing it with FastBit that it can be kept to a suitable size, or that the layout of FastBit can be arranged so as to not unduly burden the rest of the tool set. While both the solution utilized within this project and the two suggestions found just above still employ converting netCDF data to comma separated value formatted lines and feeding that to FastBit, a third possible alternative would be to alter FastBit itself so it could read netCDF directly. There is no technical reason FastBit can only interpret comma separated values, and it should be eminently possible to create native netCDF support within FastBit. This third option will require a very in depth understanding of how both netCDF and FastBit work, however, far more than is required for options utilizing already prevalent options.

Another source of continued work is the extension of the columns loaded in this manner. Currently, the ncks tool only allows for the conversion of one variable from netCDF to comma separated value format at a time. While this means that one could use ncks to create comma separated values for all of the values and coordinate dimensions of a single variable, for example converting time, depth, latitude, and longitude as well as the temperature values for the water_temp variable, one could not also convert the salinity variable simultaneously. This inherently limits the type of queries possible within our current setup, as only one variable is able to be referenced using any given query. It is possible to use ncks to export only one variable, formatted in such a way as to enable its addition to an already existing FastBit bitmap index but unfortunately there is currently no programmatic interface available within FastBit to support doing this any way other than by hand. An alteration to FastBit to enable programmatic support would be of great use in this area, or alternatively the formulation of a shell script that could perform the needed actions. Yet another alternative approach to this problem would be to try and alter the ncks tool to support the conversion of more than one variable at the same time; this, however, would require very extensive knowledge not only of netCDF but of the nco tools themselves.

In the operations category, there also remains ample room for expansion through future work. Many statistical operations exist which are still beyond the capabilities of FastBit, such as computations to find the Standard Deviation or Variance of a dataset. While this information can be found using with standard SQL operations, FastBit's limited implementation of SQL lacks the capacity to generate these values. Currently, to find the Standard Deviation of a dataset, for example, one would need to collect the output from one or more queries and then do the final computations manually. Obviously, this is an area that could be further built upon, either by implementing these capabilities into FastBit itself, or creating a process to automatically collect and compute the Standard Deviation from prepared FastBit output. Likewise, while the context of the work within this project, meteorological netCDF datasets, did not make use of heavily detailed geometric shapes, the implementation of these features is eminently possible within FastBit. Currently every point within the shape would need to be selected for explicitly, forming a long complicated series of OR'd statements. A script or built-in function of FastBit to generate these statements could prove useful for the utilization of these operations on more detailed geospatial bit mapped data.

Returning to the system architecture as proposed above in Chapter 2, much of the suggested layout has been built in the work above. One area that presents a viable source of future work, however, is the Metadata Repository. NetCDF files, by convention, hold varying amounts of metadata within their header. It should be possible to support one or more conventions for metadata layout within netCDF headers for use with the proposed Metadata Repository. Another area of possible expansion lies in the forms of output provided by the Query Processor. The interface of the project itself could also use refinement, transitioning away from the command line interface currently in use and towards the GUI initially proposed instead.

5.2 Conclusions

As has been demonstrated, the use of FastBit bitmap indexing with netCDF meteorological data offers fast and efficient search capability otherwise unavailable to users. The user can customize the generated index to emphasize certain types of queries or to better handle different sets of data. The SQL interface implemented within FastBit allows for a large amount of flexibility in the queries that can be created, and has been shown to support four classes of primitive operations. The two step filtering algorithm provides for a large speedup when utilized with the haversine function to produce efficient Range and pseudo-KNN queries. With visualization the results generated by the FastBit indexes can be projected upon either a 2D or 3D map, highlighting the region of interest. Inclusion of temporal data allowed for these maps to be animated over time, giving a user the ability to easily perceive the results of complex scientific queries.

References

[1] Chee-Yong Chan, Yannis E. Ioannidis. *Bitmap index design and evaluation*. Proceedings of the 1998 ACM SIGMOD International Conference, pages 355 - 366.

[2] Theodore Johnson. *Performance Measurements of Compressed Bitmap Indices*. VLDB 1999, pages 278 - 289.

[3] Patrick E. O'Neil. *Model 204 Architecture and Performance*. Proceedings of the 2nd International Workshop on High Performance Transaction Systems, pages 40 - 59.

[4] Alexander Rubin. *Geo Distance Search with MySQL*. http://www.scribd.com/doc/2569355/Geo-Distance-Search-with-MySQL

[5] Harry K.T. Wong, Hsiu-Fen Liu, Frank Olken, Dorom Rotem, Linda Wong. *Bit Transposed Files*. VLDB 1985, pages 448 - 457.

[6] B.S. Lee, R. Musick. *MeshSQL: the query language for simulation mesh data*. Information Sciences, volume 159, issue 3-4, 2004.

[7] Kesheng Wu, Ekow J. Otoo, Arie Shoshani. *An efficient compression scheme for bitmap indices*. ACM Transactions on Database Sytems 31:1 (2006), pages 1-38

[8] K. Shaw, J. Sample, E. Ioup, M. Abdelguerfi, O. Tabone. *Efficient Approximation of Spatial Network Queries using the M-Tree with Road Network Embedding*. SSDBM 2007.

[9] Kesheng Wu. *FastBit: an efficient indexing technology for accelerating data-intensive science*. Journal of Physics: Conference Series 16 (2005), pages 556-560

[10] E. Ioup, K. Shaw, J. Sample, M. Abdelguerfi. *Efficient AKNN spatial queries using the M-tree*. The 15th ACM International Symposium on Advances in Geographic Information Systems, 2007.

[11] Kesheng Wu, Ekow Otoo, Arie Shoshani. *On the Performance of Bitmap Indices for High Cardinality Attributes*. VLDB 2004, pages 24 - 35.

[12] Kesheng Wu, Kurt Stockinger, Arie Shoshani. *Breaking the Curse of Cardinality on Bitmap Indexes*. SSDBM 2008.

[13] FastBit: An Efficient Compressed Bitmap Index Technology. http://sdm.lbl.gov/FastBit/.

[14] Haversine Formula. http://en.wikipedia.org/wiki/Haversine_formula

[15] NCO Homepage. http://nco.sourceforge.net/

[16] NetCDF FAQ. March 10, 2009. http://www.unidata.ucar.edu/software/netcdf/docs/faq.html

[17] *NetCDF Time Conventions: A Brief History of (netCDF) Time*. http://www.unidata.ucar.edu/software/netcdf/time/recs.html.

[18] *The NetCDF User's Guide*. March 10, 2009. http://www.unidata.ucar.edu/software/netcdf/docs/netcdf.html

[19] Arc GIS 3D Analyst. www.esri.com/3danalyst.

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