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Research paper

A variable resolution right TIN approach for gridded oceanographic data

David Marks[a], Paul Elmore[a], Cheryl Ann Blain[a], Brian Bourgeois[a], Frederick Petry[a,*], Vicki Ferrini[b]

[a] Naval Research Laboratory, Stennis Space Center, MS, United States
[b] Lamont-Doherty Earth Observatory, Columbia University, Palisades, NY, United States

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ABSTRACT

Many oceanographic applications require multi resolution representation of gridded data such as for bathymetric data. Although triangular irregular networks (TINs) allow for variable resolution, they do not provide a gridded structure. Right TINs (RTINs) are compatible with a gridded structure. We explored the use of two approaches for RTINs termed top-down and bottom-up implementations. We illustrate why the latter is most appropriate for gridded data and describe for this technique how the data can be thinned. While both the top-down and bottom-up approaches accurately preserve the surface morphology of any given region, the top-down method of vertex placement can fail to match the actual vertex locations of the underlying grid in many instances, resulting in obscured topology/bathymetry. Finally we describe the use of the bottom-up approach and data thinning in two applications. The first is to provide thinned, variable resolution bathymetry data for tests of storm surge and inundation modeling, in particular hurricane Katrina. Secondly we consider the use of the approach for an application to an oceanographic data grid of 3-D ocean temperature.

1. Introduction

There exists a variety of motivations for being able to produce more accurate determinations of the oceans' seafloors. Concerns can range from the information needed to guide seabed mining to understanding fault zones for potential earthquake prediction. Reduced bottom uncertainty is also very important for oceanographic and acoustic modeling such as the use of storm surge and inundation models. This paper describes applications of data representations for the irregular, multi-resolution bathymetric data that are utilized in such models. In particular two approaches for the creation of RTIN structures from traditionally structured gridded data termed top-down and bottom-up implementations are considered and one is applied to oceanographic data. While both the top-down and bottom-up approaches accurately preserve the surface morphology of any given region, the top-down method of vertex placement can fail to match the actual vertex locations of the underlying grid in many instances, resulting in obscured topology/bathymetry.

Many multi-resolution approaches have been employed for terrain data (DeFloriani and Puppo, 1995; DeFloriani et al., 2000) by using triangular irregular networks (TINs). These allow regions of greater or lesser variability in geomorphology to be represented by increased or decreased data density respectively. The ocean floor as well exhibits similar variable structural detail. For example in order to effectively model coastal storm inundation (Posey et al., 2008), bathymetry data is required from offshore to near shore areas with increasing resolution approaching the shorelines to capture flooding potential.

An important aspect of bathymetric data distinguishing it from terrain data is the difficulty of obtaining such data. High resolution multi-beam sonar scans have provided data for less than 10% of the ocean bottoms (Becker et al., 2009) which overall constitutes some 70% of the Earth's surface. The areas between the high resolution sonar swaths may also be filled in with much lower resolution altimetry information (Smith and Sandwell, 1994). To effectively make use of data from both types of sources, multi-resolution capabilities are needed.

However an important requirement here is to maintain compatibility with many systems and models that use a gridded structure for bathymetry data. Oceanographic models such as the wave models WaveWatch3 (Tolman et al., 2000) and SWAN (Simulating Waves Nearshore) (Booij et al., 1999) are traditionally based on gridded data structures. This has led us to use right TINs (RTINs) which provide the variable storage of TINS but maintain a regular structure that is compatible with gridded approaches and storage systems. Like TINs we can thin an RTIN to maintain data values only in regions that have greater variability and obtain datasets that are much smaller in size than the original dataset.

* Corresponding author.
E-mail address: fred.petry@nrlssc.navy.mil (F. Petry).

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This is important when there are limitations on data storage and transmission.

In this paper we first provide a background on bathymetry data, its collection and use. Also we describe general approaches for representation of variable resolution data. Next we discuss two approaches for the creation of an RTIN structure for gridded data termed top-down and bottom-up implementations. We discuss why the latter is most appropriate for gridded data and describe for this technique how the data can be thinned. We describe the use of the bottom-up approach and data thinning in two applications. The first is to provide thinned, variable resolution bathymetry for tests of storm surge and inundation modeling, in particular the recent hurricane Katrina. Secondly we consider the use of the approach for an application to a different oceanographic data grid of 3-D ocean temperature. Finally we provide conclusions and directions for future research.

2. Background

2.1. Bathymetry

Traditionally bathymetric (or hydrographic) charts have been produced to support safety of surface and sub-surface navigation and usually show seafloor relief or terrain as contour lines and selected depths. Bathymetric maps may also use a Digital Terrain Model (DTM) (Blak, 2007) and artificial illumination techniques to illustrate the depths being portrayed.

Bathymetric data is typically obtained from multi-beam sonar surveys (Huff and Noll, 2007) or for shallower areas, by remote sensing LIDAR (Light detection and Ranging) or LADAR (Laser detection and Ranging) systems (Guenther, 2007). The amount of time it takes for the sound or light to travel through the water, bounce off the seafloor, and return to the sounder is used to determine the distance to the seafloor. LIDAR/LADAR surveys are usually conducted by airborne systems. Bathymetry can also be obtained from satellite radar mapping of deep-sea topography by detecting the subtle variations in sea level caused by the gravitational pull of undersea mountains, ridges, and other masses. On average, sea level is higher over such mountains and ridges than over abyssal plains and trenches (Sandwell et al., 2014). The overall utilization of bathymetric data to produce the useful gridded data is a complex process. The details of this processing is given in the standard reference the GEBCO (General Bathymetric Chart of the Oceans) Cook Book (International Hydrographic Organization, 2015).

Fig. 1 illustrates how complex the seafloor bathymetry can appear. This image is from the East Pacific showing several different ocean floor structures in close proximity: a mid-ocean ridge, a fracture zone and seamounts. The bathymetry of such a seafloor region includes areas where there is a mixture of features such as ridges, seamounts, transform faults mixed with areas that are flatter such as abyssal plains and the continental shelf. The bathymetry is then more complicated as such features require more grid points to resolve the frequency content of the features.

2.2. Limitations of rectilinear grids

The typical methodologies for bathymetry data storage, extraction and fusion are based on rectilinear gridding techniques. Common approaches to the structure of bathymetric databases are based on tiles of rectilinear grids at different resolutions, reflective of the data sources and collection eras (Ryan et al., 2009; GEBCO, 2010).

Rectangular grids, however, can have artifacts at the boundaries of tiles with different grid resolutions and data uncertainties. Discontinuities at the edges appear as differences in spatial frequencies and uncertainties of the data. For example, a 2-min tile in the Digital Bathymetric Data Base – Variable Resolution, DBDBV, (NAVOCEANO, 2012), which is largely derived from inferring the bathymetry from satellite altimetry data of the gravitational deformation of the ocean

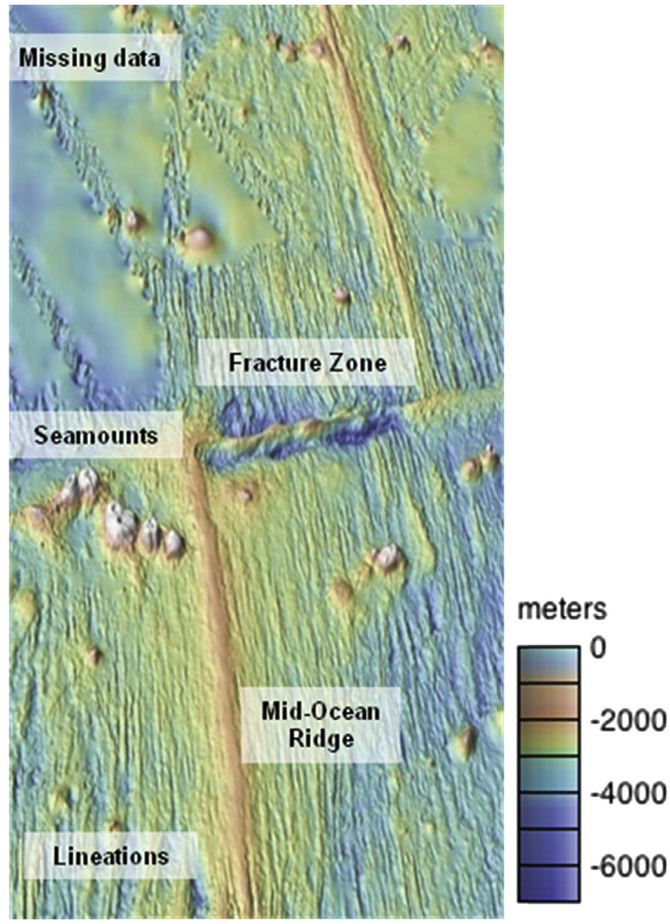

Fig. 1. Complex geomorphology near Pacific coast of North America. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

surface from mean sea level (Smith and Sandwell, 1997), possesses an uncertainty estimate of 300 m in depth and position. Closer to land, higher resolution and lower uncertainty data will intersect the 2-min data. Edge matching when interpolating across the boundary becomes problematic because a) the edge information of the higher resolution data is missing due to aliasing in the 2-min data, and b) the higher uncertainty data can report values discontinuous with the more certain data (Elmore and Steed, 2008; Elmore et al., 2012).

Further complicating the continued use of rectilinear grids are new collection techniques. Bathymetry data is now sampled at multiple resolutions and by multiple platforms, each with differing error/uncertainties profiles. Irregular sampling methodologies often are used, such as along coastlines and riverine areas or areas with sloped bottoms. In addition, data holdings in deep water commonly are at mixed data densities as modern surveys can provide very high resolution data, but can only do so in limited areas. Furthermore, rectilinear techniques also are too cumbersome for real-time storage and analysis on new collection platforms such as autonomous underwater vehicles (Eriksen et al., 2001).

To summarize, current methodologies for data storage, extraction, and merger of data sets are based on rectilinear gridding techniques fixed in grid size that are unable to produce grids with variable spacing based on differing depth regimes and underlying geomorphology. Utilizing the variable grid spacing of bathymetric data is a key need for accurate ocean modeling; high resolution is typically needed to properly render the highly variable depths of shallow water regimes as well as large changes in the bathymetric slope associated with seafloor morphologies so as to maintain numerical accuracy. Low resolution is desired for regions of the ocean that exhibit minimal variations in depth, such as deep flat areas, e.g. abyssal plains, in order to ease computational overhead (in the case of unstructured grid models) which can be achieved with TIN based structures thinned as needed. Meaningful data thinning is especially important for scenarios of low-bandwidth and transmission of information to mobile devices.

2.3. Variable resolution data representations

Data such as bathymetry or terrain data are often represented by Digital Elevation Models (DEMs) (Maune, 2007). The term elevation can refer to altitude above sea level or in the case of bathymetry sea floor depth. The DEM does not provide a value of all points in the space but a sample of values from which values at other points can determined by one of several interpolation procedures such as splines in tension (Smith and Wessel, 1990), localized regression (Calder, 2006) and kriging (Davis, 2002)

Surface approximations of gridded DEMs are most often represented as either a regular sub-grid of the original DEM or a triangular irregular network (Little and Shi, 2001). A TIN is based on the triangular partition of the 2D surface with no fixed assumption of the distribution and location of the triangle vertices (Longley et al., 2001). Each vertex will contain an elevation data value and for other points on the surface the elevation is typically determined by a linear interpolation of the three vertices of the triangle containing that point.

A number of approaches have been developed for representation of variable resolution data (Samet, 2006). The two most commonly used for spatial data are quadtrees and triangular irregular networks (TINs). A quadtree is a spatial data structure which partitions a space recursively into four equal disjoint quadrants (Pajarola, 2002). By providing an unbalanced tree structure it allows variable resolution representation of a data field (Fischer and Bar-Yoseph, 2000). The recursive subdivision is based on some stopping condition relative to the desired resolution in varying areas of the data field, but a quadtree on its own offers little interpolative assistance for points that lie outside of the initial input values. However, to determine the value of points outside of the initial input values, a quadtree's rectangular leaf cells require a bilinear interpolative approach in contrast to the simpler linear interpolator we use with the RTINs.

TIN approximations for a surface begin with choices of points that are expected to be critical in the final approximation. This is then improved by iteratively adding points to the initial triangulation. In each triangle the point that is the worst fit to the surface is found and the original value added during the iteration (Lischinski, 1994). Then the minimum angles of the triangles are maximized avoiding "skinny" triangles (Burrough and McDonnell, 1998). This process will finally produce an improved fit to the surface but with far fewer points than the large number of original source data points. Effectively this produces larger triangles over regions in which the surface is relatively regular or uniform and with more, smaller triangles fit to areas for which the surface has larger variability.

A special case of a TIN is known as the right-triangular irregular network (RTIN) which is an approximation form that is intermediate between a regular subgrid and a TIN (Evans et al., 2001). The RTIN is, like the TIN a triangulated subset of the original data points, consisting of not just arbitrary triangles but ones constrained to be isosceles right triangles. An RTIN structure provides a set of points that are interconnected by right triangles and can be variably spaced by thinning an initially dense rectilinear grid of points through various thresholding criteria. RTINs support the creation of surfaces whose resolution adapts with seafloor depth and morphology. We note the RTIN can be viewed as a $[4,8^2]$ Laves tiling (Velho and Zorin, 2001).

On the left in Fig. 2 is a colour contour of the Katrina testing region showing onshore topography (positive) and offshore bathymetry (negative) in meters. New Orleans is located at 30N and 90W, left center in the figure. The bottom of the Mississippi river delta is visible at the bottom center. On the right part are the remaining triangles of the resulting RTIN constructed from the data after thinning using a fixed metric of 10 m. Before the RTIN process this gridded dataset possessed a uniform 216 m resolution. The RTIN condensed this representation to approximately 1.3% of the number of points in the original with a RMS error of 2.5 m. Regions of high inshore and deep water variability remain densely gridded while flat regions are depicted with very large triangles and very sparse groups of points.

3. RTIN approaches

When transitioning from a single resolution input data grid to a multiresolution RTIN, two different approaches are viable. Either a top-down or a bottom-up approach can be taken, with both arriving at the same general triangular mesh surface.

Our initial effort was to utilize the first approach as it had been extensively considered for visualization applications. However while both the top-down and bottom-up approaches accurately preserve the surface morphology of any given region within a given tolerance, the top-down method of vertex placement can fail to match the actual vertex locations of the original grid in many instances, due to the constraints of the RTIN structure. All RTINs produced via the top-down method will possess a dimensionality of 2^n+1 by 2^n+1 for some whole integer n. Input data sets that do not match this dimensionality will not have their original data points preserved, and while sets where the dimensionality is

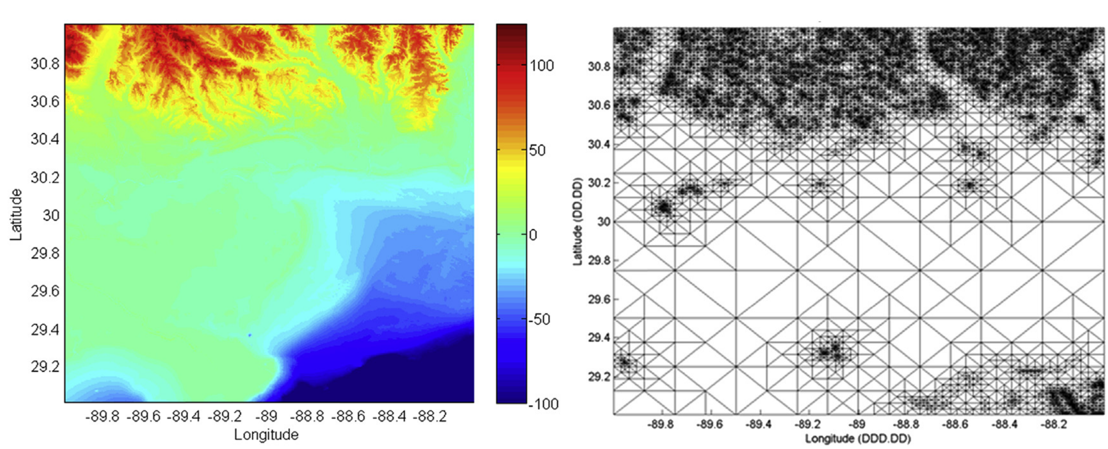

Fig. 2. Thinned RTIN bathymetry. The dark blue of the colour bar on the left indicates bathymetry depths of − 100 m or deeper. The colours above 0 on the bar indicate on-shore topography. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

matched can retain their original points in theory, in practice floating point arithmetic will mean that many original point locations will still be lost. Incorrect topography details in near shore areas could easily lead to errors in the modeling of flow and surge propagation for the storm and so the top-down approach was not further pursued.

3.1. Bottom-Up RTIN approach

Because of the issues with the above top-down approach, we turned our attention to a second approach – the bottom-up. Starting with a dense grid, points are removed while maintaining an RTIN structure. This approach begins with a fully populated RTIN structure of uniformly sized partitions matching exactly the initial input grid and a user criteria providing the basis for thinning the dense grid. Non-contributive points are located and removed from within the grid and the surrounding triangles are then merged into larger triangles, coarsening the grid (Bourgeois et al., 2015; Marks et al., 2015, 2016). As long as only two triangles are being merged together at a time, the point being removed will exist on the interior of the triangles being merged and therefore poses no danger of violating the grids core geometric properties or of needing to propagate the merge outwards into other triangles. On the other hand, however, this approach requires that the points which are removed be bordered by either two or, in most cases, four triangles and invalidates many points from being removed unless some neighboring triangles are merged first.

Since it begins with the grid at the original resolution and performs a triangulation upon it, every point retained within the thinned RTIN is an actual point present within the original data grid as well. In addition to the advantage of retaining solely original points, this approach also allows for rectangular datasets to be used as there is no imposition that the end result is a square bisected by two triangles.

3.2. Thinning approaches

One of our major goals is to provide approaches for the efficient storage of the large volume of bathymetric data. To change a dense RTIN into a variable resolution grid, the data is reduced or thinned based on threshold criteria provided by the user. Each point is analyzed for the effect its removal has on inducing error in the thinned surface when compared to the initial dense grid. If the error is below the threshold with respect to neighboring points it is removed.

Specifically we have considered two criteria to control point removal on the RTINs. The first reduction technique uses a threshold criterion from Suarez and Plaza (2009), that evaluates a point by comparing the point's value with the interpolation of the value at the point's location. If the difference between the actual value of the point and the interpolated value is within a specified threshold, the point is removed. For example with bathymetry data, using a depth threshold of 10 m, if the difference between the interpolation and the actual value is less than 10 m, the point is removed. This type of reduction allows for deep sea morphologies to be maintained, but causes sparseness in the shallow water regions.

The second reduction criteria is a percentage criteria that evaluates a point by comparing the difference between the point's value and the interpolation of the value at that point with a specified percentage of the point's original value. Intuitively this criterion can be viewed as a protective criterion for lower valued points (e.g. shallow) and thus is typically used in combination with the threshold criteria. Used alone, the criteria might remove higher valued points (e.g. deeper) while maintaining lower valued ones. This type of reduction maintains a denser grid in shallow water, but results in loss of detail for deeper sea morphologies.

To balance these two behaviors in thinning, a combined threshold approach can be used where both criteria have to be maintained before point removal. This approach maintains an acceptable point density for both shallow water and deep sea morphological regions.

4. Experiments with RTIN usage in modeling

A number of oceanographic experiments using RTIN representations have been carried out involving both bathymetry and 3-D ocean temperature data. The standard experimental approach used was to apply the bottom-up algorithm to the test data and then resample the resulting thinned RTIN to the resolution of the original test grid. This permits comparisons of the final values of the resampled grid with the original for RMS error computation purposes and to utilize the resampled grid with forecasting tools and models to gauge the effect, if any, produced by the thinning process

4.1. Inundation and surge modeling

The experimental tests in this section are designed to examine the fidelity of ocean models in accurately capturing hurricane-induced surge and inundation when configured using a range of RTIN-generated bathymetry and topography fields. The hurricane Katrina (Aug. 2005) benchmark (Blain et al., 2008) is then used for this evaluation. Model experiments run from pre-storm run-up to beyond the storms' landfall. Following hurricane Katrina, the US Geological survey recorded 458 observations of high water marks along the Mississippi and Louisiana coastal and inland regions. This data in addition to NOAA hydrograph stations at Pilot's Station, SW Pass, Louisiana, Waveland, Mississippi and Dauphin Island, Alabama are used in evaluating model performance. The Katrina benchmark also includes the best available wind forcing, NOAA's Hurricane Research Division (HRD) Real-time Hurricane Wind Analysis System (H*Wind) product. This hurricane benchmark test is chosen for the availability of observational data and the documented ocean model performance using operational coastal surge and inundation models.

4.1.1. Bathymetry RTINs for surge and inundation modeling areas

The first case was a bathymetric dataset collected from the NOAA Coast Relief Model (2014) centered on a region impacted by hurricane Katrina. A 1,050,625 point dataset, the topology & bathymetry was gridded into a 1025 by 1025 square covering a 2 degree by 2 degree swath resulting in 216.5 m resolution. A variety of different thinned RTIN meshes were produced using different thinning metrics, starting with very small criteria and gradually increasing.

Table 1 shows the Katrina bathymetry data as thinned by the combined depth and percentage criteria. The entries consist of: number of points remaining (in thousands), % reduction from original, and RMS error (m), the sample standard deviation between the thinned values and the original values.

The braking effect of the percentage metric is readily apparent when examining how slowly the number of remaining points changes when the percentage metric is held constant. Examining the RMS error values shows a correlation value of 0.65 between the eventual RMS error of the thinned mesh and the maximum amount of thinning achieved for Katrina. In general this shows that a very low RMS error is achievable with very high levels of thinning, reinforcing the need to conform the criteria used to the underlying nature of the data being thinned.

The effectiveness of using both criteria can be seen clearly by considering what occurs when only one criteria is used in thinning.

Tablee 1
Hurricane Katrina bathymetry data thinning results.

	1 m	3 m	10 m	30 m
0.03%	437 K\.58\.20	410 K\.61\.37	408 K\.61\.61	407 K\.61\1.02
0.1%	340 K\.68\.25	269 K\.74\.63	240 K\.77\1.22	240 K\.77\1.87
0.3%	295 K\0.72\.20	208 K\.80\.71	151 K\.86\1.88	144 K\.86\3.67
3%	239 K\0.77\0.27	137 K\.87\.76	69 K\.93\2.13	56 K\.94\ 6.07
10%	219 K\.79\0.29	113 K\.89\.78	43 K\.96\2.15	31 K\.97\6.10
50%	213 K\.80\.29	101 K\.90\.80	29 K\.97\2.19	16 K\.98\6.13

Specifically for the Katrina data set using only the depth criterion, values were obtained ranging as follows:

1 meter : 81% reduction\ 0.30 rms error

30 meter : 99% reduction\ 0.20.2 rms error

These values are clearly more extreme than for the combined criteria. Note in particular that the RMS error for 30 m is over 3 times greater than the worst case in Table 1. This can be seen further below, where using only the % criterion, the RMS error again is decidedly greater.

0.03% 61% reduction\1.1 rms error

50% 99% reduction\83.6 rms error

4.1.2. Hurricane surge modeling

In this section we describe evaluations of the effect of the two RTIN thinning parameters and the resulting resolution of the bathymetry on the ability of the ocean model to accurately simulate hurricane storm surge and inundation using that bathymetry. Surge refers to the over water component of the water pileup from the hurricane wind stress while inundation refers to the inland movement of that water due to the surge pileup at the shoreline.

Hurricane Katrina: The Katrina test case applies the finite element –based Advanced Circulation Model (ADCIRC) in its two-dimensional depth-integrated mode (Fleming et al., 2007). ADCIRC is a well-established, validated (e.g., Dietrich et al., 2011; Blain et al., 2010; Westerink and Coauthors, 2008) surge and inundation model.

In the Katrina experiment the ADCIRC model is used with a grid of irregular node locations. The bottom-up RTIN was created covering the modeled area and bathymetry points were interpolated to the ADCIRC node locations. Fig. 3 shows the regridded, thinned RTIN for the 10 m and 10% criteria. The residual, i.e. the difference between the depth/ altitude, for the regridded thinned RTIN and the original model grid at the original model grid locations, is near zero for most of the region, with a maximum residual of about 1.7 m.

The bathymetry grid used for the surge and inundation model covers a much larger area than the 2 degree by 2 degree area that was used to create the thinned RTIN. While the model grid centers on the northern Gulf of Mexico coastal region and encompasses surrounding inland areas, it also includes the entire Gulf of Mexico and extends out into the western North Atlantic Ocean. Such an expansive domain allows the surge to naturally build up within the modeled region as the hurricane moves from the deep ocean into coastal waters. Ocean boundaries in deep water are subject to minimal surge and inverted barometer effects and can appropriately accept tidal forcing from a global tide model. These boundaries are also far removed from the coastal area of interest. The targeted spatial resolution of the model's grid near the coast and inland is 225 m.

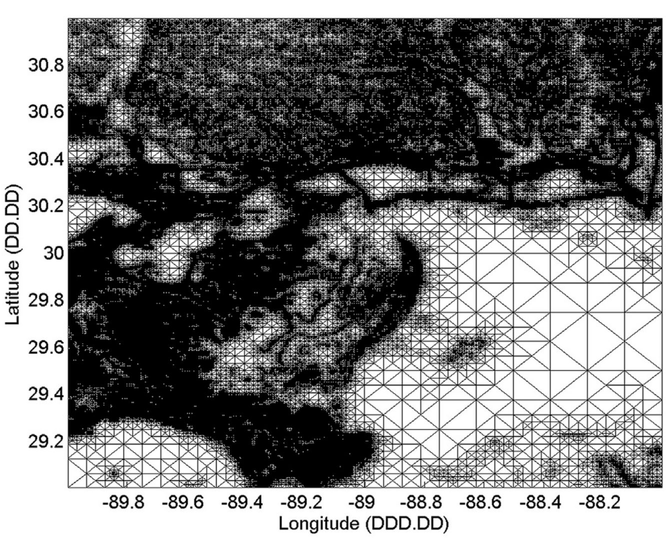

Fig. 3. Thinned bathymetry for hurricane Katrina.

Two ADCIRC surge and inundation model runs were conducted: 1) using the original model bathymetry grid, and 2) using the regridded, thinned RTIN bathymetry interpolated to the original model grid. The interpolation of the RTIN bathymetry to the model grid is a necessary step at the present time because the ADCIRC model does not utilize a native RTIN grid. The ADCIRC model grid is composed of irregular sized triangles (finite elements) with different numerical constraints on their shape (i.e., equilateral triangles) than those associated with the RTIN. The remainder of the model grid bathymetry outside of the RTIN region remains unchanged.

The elevation difference between the bathymetry on the original model grid and the regridded thinned RTIN bathymetry on the model grid shows a maximum difference of 2 m, which correlated well with the residual between the original bathymetry data grid and the regridded thinned RTIN bathymetry, indicating that the interpolation step had minimal impact. For most of the region the difference is near zero. Also the RMS error over the entire region is 0.19 m, with a maximum value of 1.5 m.

Now we can describe the water level differences between the surge and inundation model runs on the original model grid and the regridded thinned RTIN bathymetry interpolated to the model grid created using the 0.03% and 1 m metric. The water level difference at each location is computed using the *maximum* water height over the entire simulation period for each bathymetry used, i.e. original and thinned RTIN. For most of the region the difference is predominately zero, and the maximum difference is 6 m at three locations. The high value spots are at about 29.3N and 89.5W, located south of Buras, LA. but there is no evident correlation between the location of these outliers and the high residual values. The RMS error over the entire region is 0.044 m indicating overall excellent comparison between results using the different bathymetries.

4.2. Ocean model temperature experiment

Acoustic models typically require data sets that provide water temperature and salinity as these are factors for determining acoustic propagation (Jensen et al., 2011). In this example we used data from one time instance (July 11, 2013) of three-dimensional ocean temperature from a real-time nowcast over an area in the vicinity of Chesapeake Bay. The data set is composed of a horizontal grid of 296 (Longitude) by 262 (Latitude) points and has 49 vertical layers at fixed depths (ranging from 0 m to 4718 m) with a total of 86,432 temperature points. This was the first actual dataset tested possessing dimensions not expressible as 2^n+1 by 2^n+1 for some value n, where n is a whole valued integer. Fig. 4 shows representative examples of the water temperature at depths of 32 m and 296 m.

Thinning was accomplished separately on each horizontal depth layer after applying the bottom-up algorithm to create the RTINs As it was decided that using the percentage criteria to preserve shallow areas did not make sense in a temperature context, just the threshold criteria was used. The metric value was set to 5% of the lowest temperature in each elevation layer since the range of temperatures changes with depth. This helps to preserve any of the finer details of the temperature gradients. For example, if the user specified a thinning metric of 2 °C and the value of a grid point under consideration is within 2 degrees of its neighbors it would be eliminated. Fig. 5 shows the RTIN structure for the same 2 depth layers illustrating the amount of thinning that was accomplished.

Again we computed residuals by regridding the thinned grid to the original grid points using linear interpolation, and then taking the difference between temperatures on the original grid and the regridded thinned grid. Table 2 shows the statistics for residuals of four selected

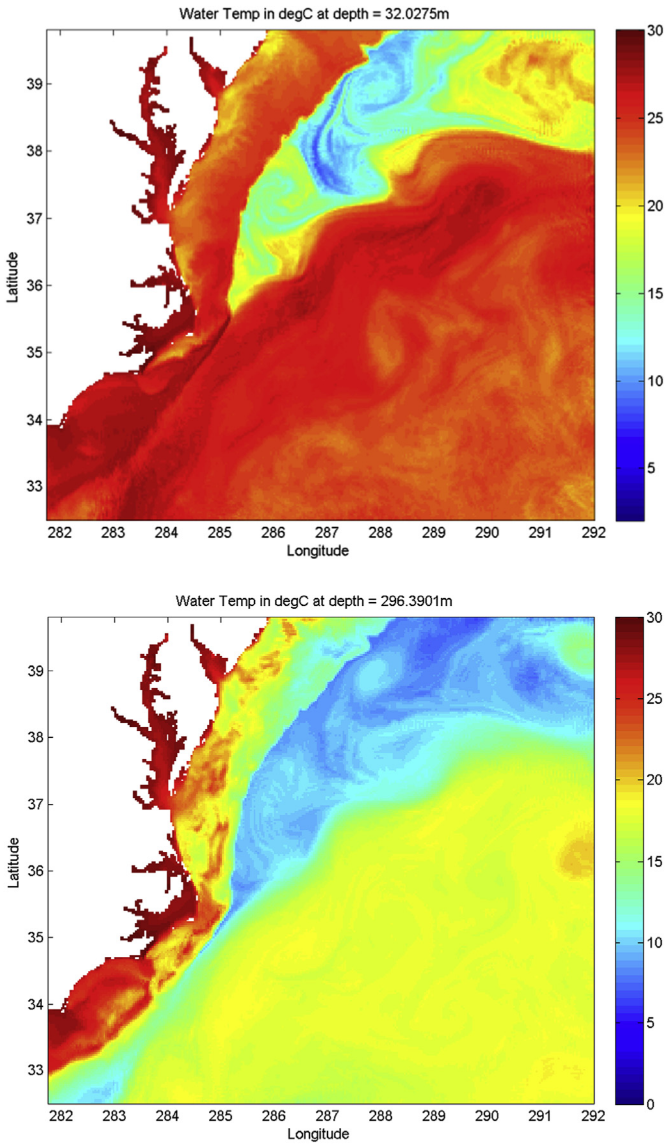

Fig. 4. Ocean temperature – depths of 32 m and 296 m. The colour bars are in units of degrees Centigrade. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

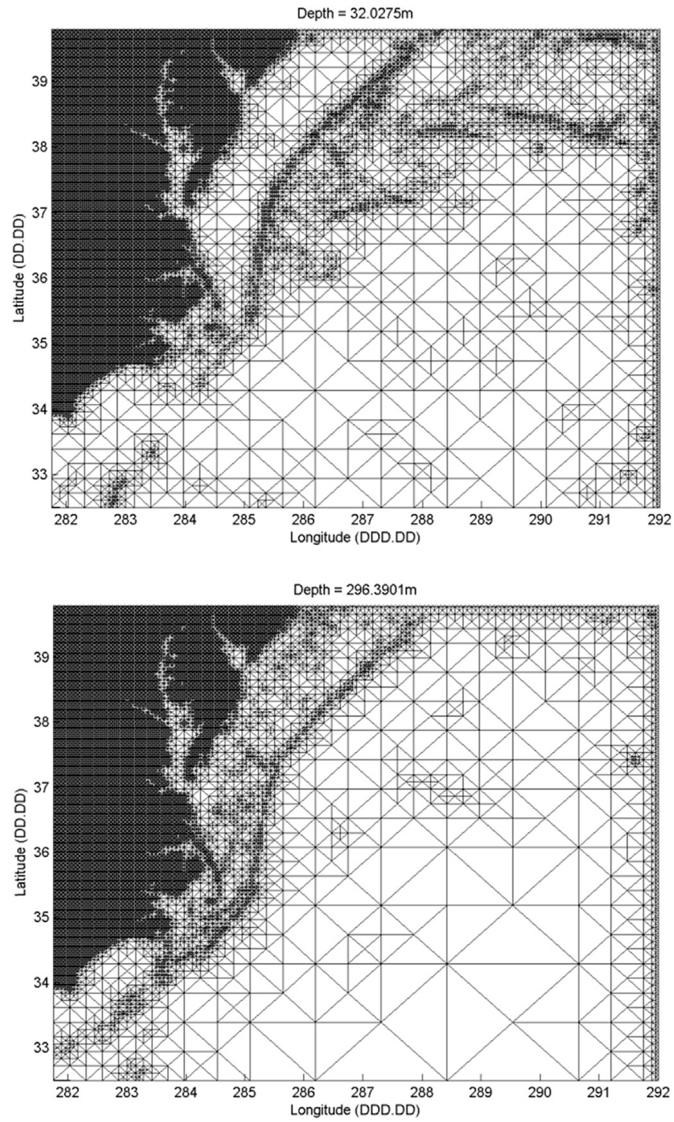

Fig. 5. Thinned RTIN structure of water temperature data from Fig. 4.

layers, the difference between the original data and the regridded thinned grid. Additionally the kurtosis for the residuals is leptokurtic (fat tailed). Table 3 shows the characteristics of the cumulative distribution function of the regridded residuals for the 4 layers. We see that for the 0 m and 2555 m depth layers that the range of values for the 95% confidence interval (CI) fall within the specified thinning criteria and that only a small percentage of the total number of points exceed the thinning criteria. The 32 m and 296 m depth layer's 95% CI exceed the thinning criteria indicating that smaller thinning criteria may be appropriate for these layers due to a large number of instances of high gradients in them.

The blue line in Fig. 6 shows the thinning metric that was used for each depth layer of the ocean temperature, which was computed as 5% of the smallest temperature value for each layer. The maximum errors are apparent in the residuals and are spatially dispersed throughout the grid versus clustering in a few locations. The red line in Fig. 6 shows the RMS error of the residual for each depth layer. The residual is nominally about 0.2 °C for the entire data set. Recall that the temperature range of this data is 2–30 °C, so the RMS error residual is about 1/10 of the smallest value, indicating an excellent retention of fidelity. The average percentage of points remaining after thinning for all layers is 6%, indicating that the thinning reduced the size of this data set by more than a factor of 10 while maintaining good fidelity.

Table 2
Regridded residual statistics.

Depth (m)	Max °C	Mean °C	RMS °C	Skewness
0	1.31	0.014	0.001	Symmetric
32	1.44	0.006	0.001	Symmetric
296	1.55	0.001	0.001	Symmetric
2555	0.42	0.001	0.0003	Moderately skewed

Table 3
Regridded residual cumulative distribution function characteristics.

Depth (m)	Thinning criteria (°C)	σ (°C)	95 CI (°C)	% < Thinning Criteria
0	0.94508	0.24	[− 0.53 0.51]	0.999
32	0.4057	0.31	[− 0.68 0.64]	0.812
296	0.36047	0.3	[− 0.67 0.62]	0.761
2555	0.13142	0.054	[− 0.099 0.126]	0.942

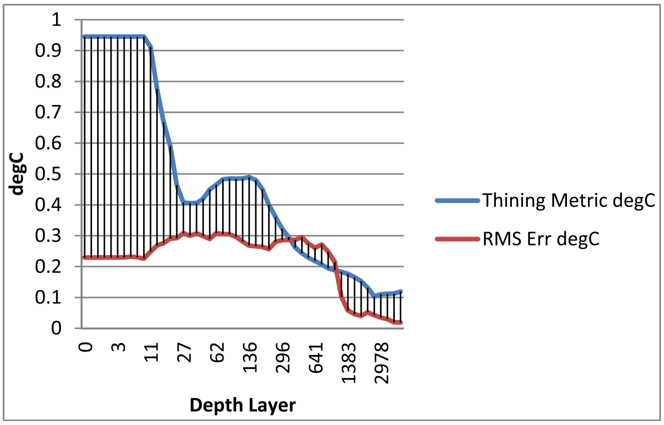

Fig. 6. Ocean temperature thinning metric and RMS error residual vs. depth. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5. Summary and conclusions

In this paper we described an approach for variable resolution bathymetry data analysis. The strength of the system is that it allows for the creation of flexible irregular mesh structures that can model any shape from regular grid spaced structures that are very common by using right triangular irregular networks (RTINs). These structures have the capability to thin dense areas of data where little data is needed while maintaining fidelity in areas of more detail. This allows for interpolation and analysis of all structures as well as the ability to convert all structures to a grid that can be exported and visualized. Finally, we discussed the use of the bottom-up approach and data thinning in two applications. The first is to provide variable resolution bathymetry for tests of surge and inundation modeling, in particular the recent hurricane Katrina (2005). Secondly we consider the use of the approach for an application to a different oceanographic data grid of 3-D ocean temperature. This is the first case of applying this approach to geophysical data that is not terrain (land & seafloor), and the results shown here provide very strong evidence that it can be applied to other forms of geophysical data.

There are a number of areas for which we feel additional research efforts are needed to fully leverage the advantages offered by the RTIN process to gridded oceanographic data. Uncertainty estimates that apply to the thinned RTIN structure need development as do criteria for thinning based on geomorphological features such as the slope. For application of RTIN to ocean models, assessments are needed regarding the compatibility and effectiveness of the variable resolution structure with operational ocean models. Future adaptive modeling strategies may be able to take advantage of the thinned RTIN bathymetries, such that they would require computations only at the RTIN point locations. An advantage to this strategy would be that computational costs of the ocean models could be reduced. Furthermore, research is needed to determine the effect variable bathymetric grid uncertainties have on models in which the RTIN is used.

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