Space-Time Cube Representation of Stream Bank Evolution Mapped by Terrestrial Laser Scanning

M. J. Starek, Member, IEEE, H. Mitasova, K.W. Wegmann, N. Lyons

Abstract— Terrestrial laser scanning (TLS) is utilized to monitor bank erosion along a stream that has incised through historic millpond (legacy) sediment. A processing workflow is developed to generate digital terrain models (DTMs) of the bank's surface from the TLS point cloud data. Differencing of the DTMs reveals that the majority of sediment loss stems from the legacy sediment layer. The DTM time series is stacked into a voxel model to form a space-time cube (STC). The STC provides a compact representation of the bank's spatiotemporal evolution captured by the TLS scans. The continuous STC extends this approach by generating a voxel model with equal temporal resolution directly from the point cloud data. Novel visualizations are extracted from the STCs to explore patterns in surface evolution. Results show that erosion is highly variable in space and time with large scale erosion being episodic due to bank failure within legacy sediment.

Index Terms— lidar point cloud, stream erosion, legacy sediment, voxel model, GRASS GIS

I. INTRODUCTION

LAND clearing for agricultural purposes following European settlement of North America resulted in upland erosion rates 50-400 times above long-term geologic rates in much of the North Carolina USA Piedmont region [1]. A considerable amount of the eroded sediment was subsequently aggraded on floodplains and impounded in the slackwater ponds behind milldams. This trapped "legacy" sediment is commonly mistaken for natural floodplain deposition and has remained largely unrecognized as a potential source of accelerated sediment erosion contributing to modern water quality impairment [2].

Terrestrial laser scanning (TLS) provides an effective means for repeated, high spatial resolution (cm to mm-scale) mapping of 3D landscape features [3], [4]. Differencing of digital terrain models (DTMs) [5] has become the standard approach for analyzing surface change from repeated scans, but with larger number of scans, individual differences provide only a limited view of the spatiotemporal pattern of the monitored process. In [3],[6], a space-time cube (STC) approach is proposed for analyzing 2.5D (one *z* value per *x*,*y* coordinate) airborne lidar time series data. This STC concept

is similar to the approach proposed for epidemiologic studies [7] or remote sensing meteorological data [8] except our methodology was developed to analyze coastal elevation evolution.

In this work, the STC approach is extended to analyze a time series of 3D TLS surveys acquired to monitor bank erosion along a stream that has incised through legacy sediment. A data processing workflow is developed to enable the measurement of surface change from the TLS point clouds. The STC approach transitions analysis from static DTMs to terrain abstraction as a dynamic 3D layer using voxel model representation. Novel visualizations are extracted from the STC to explore spatiotemporal patterns in the stream bank's evolution.

II. STUDY AREA AND TLS SURVEYS

The study area is a stream located in Raleigh, North Carolina within the Piedmont region. For this analysis, an 11.5 m wide by 3.2 m high section of bank along the outside meander bend of the stream was mapped [Fig. 1(a)]. Three distinct sedimentary layers comprise the stream bank: pre-European settlement, pre-milldam, and post-milldam [9]. The pre-European and post-milldam deposits are primarily silts and clays, whereas the pre-milldam layer is fine-to-medium sand.

A series of nine TLS surveys forming eight sequential data epochs (Table I) were acquired over an 18 month period using a Leica Geosystems ScanStation 2 mounted on a static tripod. The ScanStation 2 operates at a blue-green (532 nm) wavelength with a maximum laser pulse rate of 50,000 Hz and 300 m maximum range at 90% albedo. The scanner is a discrete return system that records one return per emitted pulse. Factory quoted position accuracy is 6 mm at 50 m range (1 σ). A rotating sensor-head with tilt compensation coupled with an oscillating mirror for horizontal and vertical beam steering enables a 360 x 270 degree maximum field-of-view.

For each survey, scans were acquired from two different positions at a resolution of 1 cm point spacing at 12 m range. The point density overlap resulted in a mean point density exceeding 1 pt/cm^2 on the exposed bank surface. Six static targets placed within the scene defined a localized coordinate frame from which to reference the scans relative to each other across the epochs. The targets consisted of aluminum pie plates painted with a reflective bulls-eye pattern for detection within the point clouds. Targets were mounted to the base of trees and located at different distances and orientations for favorable registration geometry.

M.J. Starek was with the Marine, Earth, & Atmospheric Sciences Department, North Carolina State University, Raleigh, NC 27695. He is now with the Harte Research Institute at Texas A&M University-Corpus Christi, 78412 USA (e-mail: michael.starek@tamucc.edu).

H. Mitasova, K.W. Wegmann, N. Lyons are with Marine, Earth, & Atmospheric Sciences Department, North Carolina State University, Raleigh, NC 27695 USA.

All scans were registered relative to the first survey point cloud using the Leica Cyclone registration software. Targets that degraded accuracy during a registration process were disabled but at minimum four targets were used. The registration software reports the mean absolute error (MAE) which is the average of the absolute difference in the horizontal and vertical component of control points shared between scans during a registration process. The average MAE across all surveys was estimated to be ~1.1 cm. Table I lists the MAE for each survey (end-survey for listed epochs) relative to the 12/10/2010 baseline survey.

IABLEI								
TLS SURVEY	EPOCHS	AND REGIST	RATION N	I EAN	ABSOLUTE	ERROR (MAE)	1
m: · 1	0	1.	D	1 .		MAR (>	1

Time period	Survey dates	Days between scans	MAE (cm)
Epoch 1	12/10/ 2010 to 01/29/2011	50	1.1
Epoch 2	01/29/2011 to 04/07/2011	68	0.8
Epoch 3	04/07/2011 to 08/24/2011	139	1.2
Epoch 4	08/24/2011 to 10/20/2011	57	1.1
Epoch 5	10/20/2011 to 01/31/2012	103	1.2
Epoch 6	01/31/2012 to 04/17/2012	77	1.3
Epoch 7	04/17/2012 to 06/08/2012	52	1.1
Epoch 8	06/08/2012 to 06/27/2012	19	1.2

III. METHODOLOGY

A. Data Processing

Due to the unique surface geometry and orientation of the stream bank relative to the scanner field-of-view, vegetation occlusion, and true 3D structure of the point cloud, a systematic data processing workflow was developed to measure surface change. The following steps were applied to process each survey's point cloud data:

- 1. Manually clip the stream bank region of the point cloud.
- Rotate the point cloud relative to a 2D least-squares line fit to the *x*,*y* coordinates of the first survey point cloud [4].
- 3. Transpose the *y* and *z*-axis such that the *z*-coordinate now represents the orthogonal distance to a channel oriented *x*-*y* vertical base plane from which surface change can be measured (see Fig. 2). This *z*-coordinate is referred to herein as *surface distance*.
- Filter non-surface points (e.g. vegetation) using the TIN densification filter of [10] implemented in [11] [Fig. 1(b)].
- 5. Simultaneously interpolate and smooth the filtered points using a regularized spline with tension [12] into a 1 cm-resolution digital terrain model (DTM) of surface distance values [Fig. 1(c-d)].

The result of the workflow is a time series of bare-earth DTMs representing the bank surface at time snapshot t_k , where k=1, ..., n surveys.

The data processing workflow transforms the stream bank point clouds into a 2.5D representation. This enables the application of the TIN densification filter algorithm (step 4 above), which was developed for 2.5D airborne lidar data. The filter works by generating a sparse TIN from neighborhood minima and then progressively adds points based on certain criteria in relation to the triangle that contains it [10]. To apply the filter, the parameters were adjusted to account for the TLS data density and spatial scale of the measured surface. Point clouds were textured with scanner co-aligned RGB imagery acquired during the surveys to manually segment regions of the cloud into ground and non-ground points. Parameters were tuned in an iterative process until filter results matched well (> 92% correct) with the set of segmented points.



Fig. 1. (a) Investigated section of stream bank imaged on 12/10/2010. Three distinct sediment layers, separated by the dashed lines, comprise the bank from bottom-to-top: pre-European, pre-milldam, and post-milldam (legacy). ~10 cm at top is post-legacy sediment. (b) 12/10/2010 filtered into ground and non-ground points. (c-d) DTMs generated from the first and last survey.



Fig. 2. Interpretation of the transformed, localized coordinate frame: x coordinate is distance along the stream bank, y is vertical distance, and z is orthogonal distance to the channel oriented x-y vertical base plane. Photo shows the actual channel and stream bank from the same view direction.



Fig. 3. (a) Discrete Space-Time Cube computed from DTMs. (b) Continuous Space-Time Cube computed directly from the processed point clouds.

B. Summary Metrics of Surface Evolution

Differencing of the derived DTMs was used to measure surface distance change. To estimate the volume of eroded sediment from the different layers, the DTMs were segmented based on the elevation of the disconformities separating the layers on the bank face. A trapezoidal approximation was then used to estimate volume loss for each epoch and for the entire 18 months from the differenced DTMs.

The TLS positional errors propagate directly into our

resultant DTMs. Assuming a positional error of $\sigma_z = 1.1$ cm for our DTM surface distance values, and propagating the error due to the differencing of two z measurements, $\sigma_{\text{uncertainty}} = \sqrt{\sigma_{z1}^2 + \sigma_{z2}^2}$, this equates to a vertical uncertainty in change detection of approximately 1.5 cm [5].

Spatial patterns in surface change were mapped by applying summary statistics on a per cell basis, so that each output cell in a resulting map was computed as a function of its values in the corresponding cells across the DTM time series. Using this approach several different types of raster metrics (e.g. [6]) can be generated to characterize dynamic regions of the surface.

C. Space-Time Cube Representation of Surface Evolution

Using a simple implementation of a discrete STC, the time series of DTMs was stacked into a voxel model (3D raster) [Fig. 3(a)]. Unique visualizations of stream bank surface evolution were then generated by extracting voxel model cross-sections as well as isosurfaces at specific surface distance values z = c. An isosurface, c = f(x, y, t), extracted from the surface distance voxel model represents evolution of a given distance isoline (contour) in space-time. Similarly, time series of DTM differences representing change in surface distance, $\Delta z = d$, between data epochs was stacked into a voxel model to extract isosurfaces d = f(x, y, t) showing where and when the change of magnitude d occurred.

evolution Continuous STC extends the surface characterization beyond the discrete DTM snapshots by representing the dynamic surface as a continuous trivariate function z=f(x,y,t), where time t is the third dimension and surface distance z is the modeled variable. The function f(x,y,t)is derived from the time series of m point clouds $\{(x_i, y_i, z_i), i = 1, ..., n_k\}_{t_k}, k = 1, ..., m$, where x, y, z are coordinates, n_k is number of points in the *k-th* point cloud, and t_k is the time of the survey. The data from all the point clouds are merged into a single point cloud $\{(x_i, y_i, t_i, z_i), i = 1, ..., \sum n_k\}$ that is then interpolated into a voxel model at a desired spatial and temporal resolution using a trivariate interpolation method [Fig. 3(b)]. In our application, the voxel model forms a STC of stream bank surface distance values.

A regularized smoothing spline with tension [13] was used for trivariate interpolation of the voxel model:

$$z = a + \sum_{j=1}^{N} \lambda_j \left[\frac{\sqrt{\pi}}{\varphi r} 2 \operatorname{erf}\left(\frac{\varphi r}{2}\right) - 2 \right]$$
(1)

where $r = \sqrt{(x - x_j)^2 + (y - y_j)^2 + \theta(t - t_j)^2}$ is the distance between the voxel grid point (x, y, t) and the given point (x_j, y_j, t_j) , *a* is a constant trend term, φ is the tension parameter, θ is an anisotropy parameter applied to the time dimension, λ_j are coefficients solved through a linear system

of equations, and
$$erf(\alpha) = \frac{2}{\sqrt{\pi}} \int_{0}^{\alpha} e^{-t^{2}} dt$$
 is the error function.

Open-source GRASS GIS software includes an implementation of the trivariate spline with a smoothing parameter, which is often useful for processing of noisy laser scanning data [12]. Oct-tree segmentation procedure, a 3D extension of quad-tree segmentation for bivariate interpolation presented in [12], was implemented to support processing of large number of points typical for TLS surveys. Figure 4 summarizes the data processing and analysis methodology.







Fig. 5. Estimated volume loss by sedimentary layer.



Fig. 6. Summary metrics of surface evolution: (a) Range of surface distance retreat associated with sediment loss. (b) Map of survey dates when minimum surface distance was observed. Red areas were at minimum during the last survey while blue areas were at minimum during the first survey, indicating aggradation over time. Both maps are overlaid on the first survey DTM.

IV. RESULTS AND DISCUSSION

A. Volume Change

Visual comparison of the DTMs from the first and last survey indicated substantial sediment loss, especially in the post-milldam layer [Fig. 1(c-d)]. Differencing between the individual DTMs revealed that volume change was highly variable both in space and time. Several relatively stable epochs were interrupted by epochs with large, localized losses of sediment. Fig. 5 shows volume loss by sedimentary layer for successive survey epochs. The majority of loss occurred during the 3rd survey epoch (Table I), which corresponded to the interval of highest rainfall intensities and stream discharge events recorded during the survey periods. Overall, a total of approximately 12.1 m³ of sediment was lost between the first and last survey. This volume of stream bank sediment loss was similar on a per-meter length of channel (0.7 m³ m⁻¹ yr⁻¹) to recent calculations relying upon planimetric erosion pin surveys from a neighboring stream also incised into millpond legacy sediments [9].

B. Spatial Pattern of Surface Change

To characterize spatial patterns in the evolution of the stream bank, the DTM time series was used to compute the range of surface distance change. Surface loss occurs for a given grid cell when the time (survey date) of surface distance minimum $Z_{\rm min}$ > time of surface distance maximum $Z_{\rm max}$. As shown in Fig. 6(a), the largest retreat in surface distance occurred within the lower section of the post-milldam sediment layer. Figure 6(b) shows the time of surface distance minimum. The post-milldam layer is particularly interesting because it experienced large sediment loss during the 3rd epoch but minimal change thereafter; however, the time at minimum is noisy within this layer reflecting redistribution of small amounts (few cm-level) of sediment, small unfiltered vegetation, and measurement error.

Surface gain occurs for a given grid cell when time of $z_{\rm min}$ < time of $z_{\rm max}$. Regions where surface gain occurred were small and indicate the possibility of either sediment accumulation from failed material not yet removed by water flow, or stream-induced sediment deposition at the base of the slope. Surface gain and loss can also stem from differences in unfiltered vegetation cover between surveys or the filter could cut parts of the actual surface. Estimates of surface gain or loss based on range differ from simple differencing of the first and last surveys by incorporating all DTMs in the time series. For example, if an eroded area was later filled with sediment, this would be captured in the range-derived maps but missed in the last minus first survey difference.

C. Spatiotemporal Patterns in Space-Time Cube

A discrete STC with variable time interval was used for compact representation and visual analysis of spatiotemporal patterns. Figure 7 shows horizontal and vertical time slices extracted from the voxel model to visualize temporal evolution of the surface within and across the distinct sedimentary layers that comprise the stream bank. The crosssections show that the massive change associated with the hydrologic events during Epoch 3 (Table I) were preceded and followed by periods of relative stability in the post-milldam sediment layer of the bank. In contrast, the lower sections of the bank exhibited smaller changes distributed over several epochs with the largest losses observed in the last two epochs.

This was further highlighted by isosurfaces representing the

evolution of surface distance isolines. Figure 8(a) shows the evolution of a 2.0 m distance isoline that was mostly confined to the boundary of the post-milldam sediment layer during the first survey. Over time the stream bank started losing sediment within this region resulting in a decrease in surface distance. As a consequence, the isosurface is forced to migrate spatially towards the lower part of the stream bank. Change in surface distance between epochs was draped over the isosurface to characterize the sediment loss or gain over time.

In comparison, Fig. 8(b) shows a 2.0 m isosurface extracted from a voxel model generated directly from the time series of processed point cloud data using the trivariate interpolation method of (1). Time resolution of the voxel model was set to 51 days to align closely with the varying time intervals of the surveys. The result is a smoother representation of isosurface evolution compared to the discrete case shown in Fig. 8(a). The temporal gradient (rate of change in surface distance) was computed directly from (1) and draped over the isosurface. As observed in Fig. 8(b), the rate of loss was higher than the rate of gain as would be expected for an incised stream bank.

As another example, a discrete STC of surface differences was used to study the spatiotemporal pattern of a given value of surface distance change. Figure 9 shows isosurfaces representing 0.5 m loss (when and where 0.5 m loss occurred), with the most extensive area within the legacy sediment during the 3rd survey epoch. Several smaller areas are associated with the pre-milldam layers and the two most recent epochs.



Fig. 7. STC slices extracted from the voxel model overlaid on the first survey DTM. The horizontal slice cuts through pre-European sediment, and the vertical slices cut across all layers. Bank failure is evident in the vertical slice.



Fig. 8. (a) Isosurface for a 2.0 m distance extracted from discrete STC showing its spatiotemporal evolution. The isosurface is colored by the change

in surface distance between epochs. The lines indicate the shape and temporal location of the 2.0 m distance isoline during the surveys 1, 3, 4, 6. (b) Isosurface for a 2.0 m distance extracted from a continuous STC. Temporal resolution is 51 days, and isosurface is colored by rate of change.



Fig. 9. Isosurface for a 0.5m distance change showing its temporal evolution spatially along the bank surface (colored by time). The isosurface is extracted from the space-time cube of surface distance differences.

D. Discussion

TLS enables high accuracy 3D measurements of stream bank evolution at orders of magnitude higher spatial resolution compared to manual survey methods, such as erosion pin studies. The TLS data captured the spatial variability in large scale erosion and small scale (cm-level) changes in surface material. A further improvement is that TLS made it possible to quantify the volume of sediment loss as a function of stratigraphic unit. This is important for estimating the percent contributions of fine-grained (<64 μ m) sediment from different layers delivered to the stream as it is this grain-size fraction that contributes most to regional stream turbidity impairment.

The data processing and analysis workflow can be directly applied to measure surface change over much longer reaches of stream than examined here. The efficiency of TLS for mapping stream banks over longer distances (e.g. kilometer) will depend on the scanner characteristics, most notably effective range, and terrain complexity among other factors.

STC cross-sections and isosurfaces can both aid in visualizing surface evolution as well as reveal connections to the physical processes that underlie the observed change. For example, the contrast between the episodic erosion event that occurred in the post-mill dam section and continuing smaller changes in the older sediments is evident in the cross-sections of Fig. 7 and isosurfaces of Fig. 8 and 9. As observed, there is an abrupt spatially extensive change associated with the 3rd epoch in the post-milldam layer followed by more gradual losses in the two bottom layers over the more recent surveys. This indicates different controlling processes, such as seepage and fluvial erosion. In this way, certain physical processes can generate characteristic isosurface shapes (patterns) of surface evolution. These characteristic patterns can potentially be searched for within a STC of terrain evolution, such as within a classification regime, to detect certain processes underlying observed landform change.

The discrete STC provides a compact representation of the DTM time series derived from the TLS surveys. It is a snapshot representation of surface evolution where the time interval is variable dependent on the survey period. In contrast, the continuous STC enables uniform time intervals

through trivariate interpolation. This provides a smoothed (continuous) representation of surface evolution. Furthermore, spatiotemporal gradients (vectors of fastest surface change) can be directly extracted through (1) [see Fig. 8(b)] to further explore the relation between surface evolution and the underlying physical processes. The applicability of the continuous STC for modeling evolution of the surface between surveys will depend on the temporal resolution of the data and the underlying dynamics driving the surface change.

V. CONCLUSION

A raster and STC methodology for analysis of stream bank evolution captured by TLS surveys was presented. The data processing workflow transforms TLS point cloud data into DTMs to measure surface change. The STC approach transitions analysis from static portrayal to terrain abstraction as a dynamic 3D voxel model. Raster-based metrics and voxel-based visualizations revealed that erosion at the study site was highly variable in space and time with the largest observed erosion due to bank failure within the legacy sediment layer. The methodology presented here is general and can be used with any software that supports 2D and 3D raster data processing, trivariate interpolation, and volume visualization. Our implementation was based on open-source GRASS GIS.

VI. ACKNOWLEDGEMENT

Support of this work by the US Army Research Office grant W911NF1110146 is gratefully acknowledged.

REFERENCES

- S. W. Trimble, "A Volumetric Estimate of Man- Induced Soil Erosion on the Southern Piedmont Plateau", in *Present and Prospective Technology for Predicting Sediment Yields and Sources*: U.S. Agricultural Research Service ARS-S-40, p. 142-152, 1975.
- [2] R.C. Walter and D.J. Merritts, "Natural Streams and the Legacy of Water-Powered Mills", Science, v. 319, no. 5861, p. 299-304, 2008.
- [3] M.J. Starek, H. Mitasova, E. Hardin, K. Weaver, M. Overton, and R.S. Harmon, "Modeling and Analysis of Landscape Evolution Using Airborne, Terrestrial, and Laboratory Laser Scanning," *Geosphere*, v. 7, p. 1340-56, 2011.
- [4] M.A. O'Neal and J.E. Pizzuto, "The Rates and Spatial Patterns of Annual Riverbank Erosion Revealed Through Terrestrial Laser-Scanner Surveys of The South River, Virginia," *Earth Surface Processes and Landforms*, 2010.
- [5] J.M. Wheaton, J. Brasington, S.E. Darby, and D.A. Sear, "Accounting for Uncertainty in DEMs from Repeat Topographic Surveys: Improved Sediment Budgets," *Earth Surface Processes and Landforms*, v. 35, p. 136-156, 2010.
- [6] H. Mitasova, E. Hardin, M. J. Starek, R.S. Harmon, M. Overton, Landscape dynamics from LiDAR data time series, in Proceedings of Geomorphometry, Redlands, CA, 2011.
- [7] M.J. Kraak and P.F. Madzudzo,"Space Time Visualization for Epidemiological Research," in *Proceedings, 23nd International Cartographic Conference ICC: Cartography for Everyone and for you*, Moscow, Russia: International Cartographic Association, 2007.
- [8] U.D. Turdukulov, M. Kraak, and C.A. Blok, "Designing a Visual Environment for Exploration of Time Series of Remote Sensing Data," in *Search for Convective Clouds: Computers & Graphics*, v. 31, no. 3, 2007.
- [9] R.Q. Lewis, "The Lasting Impacts of Post-Colonial Agriculture and Water-Powered Milldams on Current Water Quality, Umstead State Park, Wake County, North Carolina" [M.S. Thesis]: North Carolina State University, Raleigh, 178 p., 2010.
- [10] P. Axelsson, "DEM Generation from Laser Scanner Data Using Adaptive TIN Models," *International Archives of Photogrammetry and Remote Sensing*, v. 33, 2000.
- [11] M. Isenburg, "LAS Tools Ground Point Filter," www.cs.unc.edu/~isenburg/lastools/, accessed on 11/2011.
- [12] H. Mitasova, L. Mitas, and R.S. Harmon, "Simultaneous Spline Interpolation and Topographic Analysis for Lidar Elevation Data: Methods for Open Source GIS," *IEEE GRSL* v. 2 (4), pp. 375-379, 2005.

[13] Mitasova, H., L. Mitas, L., B.M. Brown, D.P. Gerdes, and I. Kosinovsky, "Modeling spatially and temporally distributed phenomena: new methods and tools for GRASS GIS," *International Journal of GIS*, v. 9, no. 4, p. 443-446, 1995.