Automated measurement of eroding streambank volume from high-resolution aerial imagery and terrain analysis

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Automated measurement of eroding streambank volume from high-resolution aerial imagery and terrain analysis

Abstract
Excessive sediment is an important form of surface water impairment throughout the continental United States. Numerous studies have investigated the role of upland soil erosion as a source of sediment and phosphorus, but contributions of streambank erosion are still poorly understood. Current methods such as delineation and automated channel planform morphometric models are either too time-intensive, or do not provide adequate spatial resolution to measure smaller rivers over large scales. To estimate sediment contributions from river migration on large scales, we have created the Aerial Imagery Migration Model (AIMM), a Python and ArcPy based automated channel migration model designed to estimate volumes of erosion and deposition related to channel migration. AIMM utilizes the Normalized Difference Water Index (NDWI) to derive binary representations of river channels from aerial photography. The location of the channel is then compared between two time periods to identify zones of erosion and deposition and the volume loss related to channel migration is then calculated using a LiDAR-derived DEM. When compared to three delineations and the RivMAP model in the South Fork Iowa River watershed, AIMM was found to have a 98% agreement with RivMAP, 79% agreement with delineations, and predicted net sediment flux that was within one standard deviation of the mean prediction from the delineation analysis. Where public imagery is available, AIMM can be widely applied to estimate volumes of sediment loss in a time and cost-efficient procedure. In particular, the use of AIMM within the project-planning phase of conservation efforts could help focus resources in areas where they can have the most impact.

Keywords
Remote sensing, Aerial image and DEM analysis, Channel Migration, Erosion volume estimation

Disciplines
Environmental Monitoring | Natural Resources and Conservation | Natural Resources Management and Policy | Sedimentology

Comments

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Automated measurement of eroding streambank volume from high-resolution aerial imagery and terrain analysis

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1. Introduction

Although lateral channel migration is a natural process in meandering single-threaded rivers, bank erosion associated with channel migration can be a major source of sediment to downstream water bodies, particularly in regions that have experienced channel incision (Bosch et al., 2008; Fox et al., 2016; Purvis et al., 2016; Simon and Klimetz, 2008). Excessive sediment loads have led to a multitude of issues, including the deterioration of aquatic habitats and increased infrastructure maintenance costs related to dredging and flood control (Gray et al., 2014; Larsen et al., 2007; Pégy et al., 2005; Quist and Schultz, 2014). In addition, channel migration adjacent to roads, bridges, pipelines, and other essential infrastructure seriously threatens the integrity of these systems. Such threats are particularly acute within agricultural landscapes where agricultural expansion, channel straightening, and subsurface drainage have increased the flashiness and stream power of waterways (Beck et al., 2018; Montgomery, 2012; Schottler et al., 2014; Simon and Rinaldi, 2006). Considerable research has focused on quantifying the role of bank erosion within river sediment budgets (Beck et al., 2018; Day et al., 2013a; Noonan, 2016; Zaimes et al., 2008). Estimating the magnitude of bank erosion within watersheds greater than 10,000 km² in size, however, has presented a challenge because of the large area that must be surveyed.

Within smaller channels, erosion pin studies are a common method for observing bank erosion (Beck et al., 2018; Fox et al., 2016; Kronvang et al., 2012; Noonan, 2016; Zaimes et al., 2008). Although this method provides high temporal resolution and can provide detailed measurements, this method becomes time and cost prohibitive as the area of interest grows. Multi-temporal aerial Light Detection and Ranging (LiDAR) surveys coupled with digital elevation model (DEM) differencing have also been shown to provide highly accurate measurements of channel migration (Day et al., 2013a, 2013b; James et al., 2012). Currently, however, the high cost of these surveys has limited the number of locations where region-wide repeat LiDAR surveys have been conducted. Unlike LiDAR surveys, aerial image surveys conducted by state and national agencies, such as the National Agriculture Imagery Program (NAIP), provide adequate levels of both temporal and spatial resolution to track bank erosion within a range of stream orders and are conducted regularly. Most studies that use aerial imagery analysis to

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estimate bank erosion do so by hand delineating channel boundaries within sequential images (Fisher et al., 2013; Grabowski and Gurnell, 2016; Gurnell, 1997; Gurnell et al., 1994; Tomer and Van Horn, 2018) (Fig. 1). In a recent study by Tomer and Van Horn (2018), this methodology was used to determine the total area of bank erosion within the South Fork Iowa River (SFIR) watershed, and was then paired with a LiDAR-derived DEM analysis to estimate a net sediment flux from channel migration. Although this manual technique can achieve reasonably high accuracy, its application in reaches greater than 100 km in length is time prohibitive. Also, there is a high degree of subjectivity associated with delineations that can limit the reproducibility of these studies (James et al., 2012). These restrictions indicate that a cost-effective and reproducible methodology is needed if the regional contribution of channel migration to river sediment budgets is to be determined.

To overcome these issues, many studies have used automated channel planform models that create faster and more objective estimates of river morphometrics (Isikdogan et al., 2017; Monegaglia et al., 2018; Rowland et al., 2016; Schwenk et al., 2017). Both Rowland and others (2016) and Schwenk and others (2017) provide a summary of many such models, and an updated version of these comparisons can be found in Table 1. Although these models vary in their approaches, most of them rely on binary channel masks as inputs that are either generated internally or externally. These binary representations are then further processed using a variety of techniques to estimate migration rates, sinuosity, width, channel length, curvature, and other planform morphometrics. Although these models can be useful tools for tracking planform morphometry, the current models available are not designed to estimate the sediment budget associated with river migration.

The two main reasons that previous models are not effective estimators of this sediment flux are (i) current models that create their own channel masks do so using spectral data that are not available at the spatial resolutions required to detect smaller rivers and streams and (ii) most of these models do not measure the volumes of sediment loss associated with river migration. Other than our proposed model, the models listed in Table 1 either use multispectral imagery or hand delineations to create their channel masks. Currently, however, the publicly available multispectral datasets with the highest spatial resolution, Sentinel-2 and Landsat 8, have spatial resolutions of 10 m and 15 m respectively. Because adequate handling of georeferencing errors often necessitates that migration that is similar to the pixel size must be excluded from the analysis (Mount et al., 2003), these methods cannot measure channel migration that is less than 10–15 m. As noted above, however, current aerial imagery datasets such as NAIP now have meter to sub-meter spatial resolution, allowing for the detection of channel movement that is greater than one meter. Models such as SCREAM and RivMAP that do not generate their own channel masks would also benefit from finer resolution techniques for automatically generating channel masks, because this would increase the scope of their applicability.

In addition to their coarse spatial resolutions, most of these models do not assess migration in terms of volume and instead focus on tracking planform changes. Although this approach is useful in many contexts, estimating the volumes of sediment flux associated with channel migration is a necessary component of river sediment load calculations. We believe that a model capable of using the techniques of previous channel migration models, such as SCREAM, PyRIS, and...
RivMap, that is also designed to use high-resolution aerial imagery and a volume-based approach would be an effective tool for estimating river migration and sediment flux on larger scales.

Herein we describe the Aerial Imagery Migration Model (AIMM), a Python and ArcPy-based automated model designed to estimate volumes of erosion and deposition associated with channel migration. We also

<table>
<thead>
<tr>
<th>Package</th>
<th>Platform</th>
<th>Inputs</th>
<th>Outputs</th>
<th>Migration map</th>
<th>Volume calculation</th>
<th>Reference</th>
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<tr>
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<td>Proprietary</td>
<td>Time separated DEMs</td>
<td>DEM of difference</td>
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<td>Yes</td>
<td>Wheaton et al., 2010</td>
</tr>
<tr>
<td>SCREAM</td>
<td>IDL</td>
<td>Channel masks</td>
<td>Planform metrics</td>
<td>Yes</td>
<td>No</td>
<td>Rowland et al., 2016</td>
</tr>
<tr>
<td>ChanGeom</td>
<td>IDL</td>
<td>Channel masks and DEM</td>
<td>Centerlines, planform metrics</td>
<td>No</td>
<td>No</td>
<td>Fisher et al., 2013</td>
</tr>
<tr>
<td>RivaMap</td>
<td>Google Earth Engine</td>
<td>Multispectral images</td>
<td>Channel masks, width estimates</td>
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<td>No</td>
<td>Isikdogan et al., 2017</td>
</tr>
<tr>
<td>RivMAP</td>
<td>Matlab</td>
<td>Channel masks</td>
<td>Centerlines, planform metrics</td>
<td>Yes</td>
<td>No</td>
<td>Schwenk et al., 2017</td>
</tr>
<tr>
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<td>Python</td>
<td>Multispectral images, or channel masks</td>
<td>Centerlines, migration vector, sediment bar dynamics</td>
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<td>No</td>
<td>Monegaglia et al., 2018</td>
</tr>
<tr>
<td>RIMARS</td>
<td>Matlab</td>
<td>Multispectral images</td>
<td>Centerlines, planform metrics</td>
<td>No</td>
<td>No</td>
<td>Shahrood et al. 2019</td>
</tr>
<tr>
<td>RivWidthCloud</td>
<td>Google Earth Engine</td>
<td>Multispectral images</td>
<td>Centerlines, width</td>
<td>No</td>
<td>No</td>
<td>Yang et al. 2020</td>
</tr>
<tr>
<td>AIMM</td>
<td>Arcpy and Python</td>
<td>RGBI images or channel masks, DEM, and centerline</td>
<td>Channel masks, migration map, volumes of sediment loss</td>
<td>Yes</td>
<td>Yes</td>
<td>This publication</td>
</tr>
</tbody>
</table>

RivMAP, that is also designed to use high-resolution aerial imagery and a volume-based approach would be an effective tool for estimating river migration and sediment flux on larger scales.

Herein we describe the Aerial Imagery Migration Model (AIMM), a Python and ArcPy-based automated model designed to estimate volumes of erosion and deposition associated with channel migration. We also

![AIMM Flowchart](image)

Fig. 2. AIMM flowchart. AIMM requires four inputs (two aerial images, a DEM, and a centerline file) and produces a raster and polygonal output. AIMM can be broken down into three primary steps: (i) thresholding of an NDWI image, (ii) overlaying the two binary images to measure migration and (iii) measuring local height difference around each erosional and depositional polygon.
compare AIMM's planform methodology to RivMAP and three iterations of bank delineations to assess the relative agreement between these methodologies. Furthermore, we compare AIMM's volume estimate to methods used by Tomer and Van Horn (2018), several alternative methodologies, and DEM-derived channel profiles. AIMM's optimized use of high-resolution aerial imagery and DEM data to estimate volumes of erosion and deposition in conjunction with its relatively low processing times represents a novel and useful methodology for monitoring channel migration at high spatial resolutions over a large extent.

2. Methods

The Aerial Imagery Migration Model (AIMM) is designed to estimate volumes of erosion and deposition associated with channel migration and is composed of several python scripts that utilize the proprietary ArcPy package created by ESRI. The scripts that comprise AIMM are freely available within a GitHub repository. AIMM estimates volumes of erosion and deposition via a three-step process (Fig. 2). First, binary rasters representing the extent of river channels are derived via the thresholding of Normalized Difference Water Index (NDWI) images from sequential years. Second, zones of erosion and deposition are identified by overlaying the binary rasters to track the migration of the channel (Fig. 3). Third, the volume of each erosional and depositional zone is calculated by multiplying each zone's area by a bank height estimated via DEM analysis (Fig. 4). AIMM produces three outputs: rasters representing the binary channel masks from both input images, a migration raster that results from overlaying the channel rasters, and polygons of the erosional and depositional zones with associated volumes. The binary channel masks are included to allow users the option to use these channel masks as inputs for other planform migration models that compute metrics not included within AIMM. This section provides an in-depth description of the AIMM workflow and describes our efforts to compare AIMM with previous methodologies.

2.1. AIMM planform migration

AIMM requires two aerial images of the study area that contain red, green, blue, and near-infrared (RGBI) bands, and are sufficiently temporally separated to display migration that is greater than one pixel in size, a corresponding DEM, a river centerline dataset with associated stream orders, and an estimation of stream width by Strahler stream order (Strahler, 1957). River centerlines and width estimates by Strahler stream order are combined to create a buffered centerline dataset used to constrain training data for the threshold analysis and to remove spurious zones of erosion and deposition that are far from the channel. Although using previously derived centerlines does introduce some bias, this concern is outweighed by the large increase in model accuracy provided. Representative wetted widths are estimated by stream order via visual inspection of randomly selected reaches within the study area.

The NDWI binary classification approach for detecting waterways that AIMM utilizes was modified from previous studies that used NDWI indices to detect waterbodies and monitor channel migration (Du et al., 2016; McFeeters, 1996; Monegaglia et al., 2018; Rowland et al., 2016; Sarp and Ozcelik, 2017; Yang et al., 2018). Unlike these studies, however, AIMM primarily uses aerial instead of satellite imagery. This allows AIMM to work at higher spatial resolutions at the expense of temporal and spectral resolution. The NDWI rasters were calculated according to the raster band formula:
Green − NIR
Green + NIR

The output NDWI rasters contain floating-point values between −1 and 1, with higher values representing cells with higher water content. It was found however that the amount of computer memory needed to store these rasters was prohibitively large, so the original NDWI images are converted to normalized 8-bit integer values to reduce file size.

These NDWI rasters are then classified into binary images representing land and water classes using Li's global minimum entropy technique (Li and Lee, 1993). Li's technique is used because it has generally been found to be an effective thresholding technique, is unsupervised, does not assume a bimodal distribution, and is effective when class sizes are uneven (Chen, 2004). A random subset of five million NDWI values within a twice-width buffer of the river centerline is used to determine the thresholds for each image (Fig. 5). This process is then reiterated fifty times and the median threshold for each year is used as the final threshold to minimize the effect of sample bias. Similar to Monegaglia et al. (2018), binary noise is removed from these rasters using a set of morphological operations followed by the removal of all contiguous water regions less than 10 pixels in size. The resulting rasters are then overlaid, creating a two-bit raster with four categories corresponding to each unique combination of the land and water classifications. Land to land, water to water, land to water and water to land classifications were interpreted as stable land, stable channel, erosion, and deposition respectively. In cases where channel migration exceeded channel width, an erroneous zone of stable land was created. To address this issue, all stable land zones that did not touch a zone of stable channel were reclassified as erosion. Also, to remove erroneous zones of erosion and deposition outside of the floodplain, all contiguous land and water areas were reclassified as channelized.

Fig. 4. Relative height calculation. Bank height for erosional zones (red) was estimated as four times the standard deviation of the elevation values within the zone and the bank height for depositional zones (yellow) was estimated as the difference between the minimum zone elevation value and median elevation value.

Fig. 5. Threshold selection. The calculated Li's entropy threshold, represented by the dashed lines, was used to partition the NDWI images into land and water classifications. The distributions of the training data were roughly bimodal but had a much stronger peak within the land classification.
zones of stable channel, erosion, and deposition that did not intersect a twice-width buffer of the stream centerline were reclassified as stable land. If desired, externally generated binary channel masks can be used as alternate inputs for AIMM. This could be desirable in cases where the user has previously generated channel masks, or in cases where data with higher spectral resolution, that also has sufficient spatial resolution, allows for the generation of more accurate channel masks.

2.2. AIMM bank height estimation

Volume was calculated for each zone of erosion and deposition by multiplying the area of each zone by an estimated bank height (Fig. 4). Several methods for determining bank height for zones of both erosion and deposition were considered and the method selected was that which best predicted bank height when compared to visual inspection of cross-sectional profiles derived from a 100 m transect of a 2 m LiDAR-derived DEM (ISU, 2009). For erosional banks, multiplying the standard deviation of the elevation values within the polygon by four was found to be the best estimator, and the difference between the median elevation value and the minimum elevation within the zone was found to be the most accurate method for estimating depositional bank height. Once the best methods for estimating erosional and depositional bank heights were determined, these methods were implemented within AIMM in a fully automated manner.

2.3. Method comparison

To assess the performance of our model, AIMM was used to estimate the total volume of sediment loss within the South Fork Iowa River (SFIR) watershed in North Central Iowa (Fig. 6) between the springs of 2002 and 2009. These results were then compared with prior work and with the outputs of several other methodologies to assess the performance of AIMM. The SFIR watershed contains three main branches: the South Fork Iowa River, Tipton Creek, and Beaver Creek and has a total watershed area of 798 km². The SFIR was selected for this analysis because this watershed has been the subject of many recent studies (Tomer et al., 2008a,b; Tomer and James, 2004; Tomer and Van Horn, 2018; Yan et al., 2010), contains active channels that are much narrower (10 to 30 m) than those typically analyzed in automated river planform studies, and is known to have undergone a major channel-forming event in the spring of 2008 (Hubbard et al., 2011). As detailed in Table 1, no existing tool includes all the functionality found within AIMM, but corresponding methods were used to assess each component of AIMM. These include: (1) a comparison with hand delineation and RivMAP (Schwenk et al., 2017) to assess AIMM’s channel mask generation and identification of planform change; (2) a comparison with the bank height estimation methods of Tomer and Van Horn (2018) and streambank profiles derived from a LiDAR DEM to assess AIMM’s bank height estimation; and (3) a final comparison with the total volume loss estimated via hand delineation.

Duplicating the study extent and data used in Tomer and Van Horn (2018), all analyses were performed using spring aerial imagery from 2002 and 2009 provided by the Iowa DNR (Iowa Department of Natural
Table 2
Agreement and Cohen’s K. Full agreement results for the Delineation and AIMM migration maps by percent agreement and Cohen’s Kappa.

<table>
<thead>
<tr>
<th>Rater 1</th>
<th>Rater 2</th>
<th>Cohen’s K</th>
<th>% Agreement</th>
</tr>
</thead>
<tbody>
<tr>
<td>User 1</td>
<td>AIMM</td>
<td>0.59</td>
<td>80%</td>
</tr>
<tr>
<td>User 2</td>
<td>AIMM</td>
<td>0.57</td>
<td>79%</td>
</tr>
<tr>
<td>User 3</td>
<td>AIMM</td>
<td>0.55</td>
<td>77%</td>
</tr>
<tr>
<td>User 1</td>
<td>User 2</td>
<td>0.79</td>
<td>89%</td>
</tr>
<tr>
<td>User 1</td>
<td>User 3</td>
<td>0.78</td>
<td>88%</td>
</tr>
<tr>
<td>User 2</td>
<td>User 3</td>
<td>0.79</td>
<td>88%</td>
</tr>
</tbody>
</table>

Average Users AIMM
% Agreement 88% 79%
Cohen’s K 0.78 0.55

Resources, 2009). This imagery has spatial resolutions of 1 m and 0.61 m, respectively, and measured horizontal accuracies of 3 m at a 95% confidence interval. Tomer and Van Horn (2018) noted that the migration rates during this period were greater than that of the imagery’s spatial resolution (1 m). Also, Tomer and Van Horn (2018) noted that although there was a major channel forming event in 2008, river stages during the 2002 and 2009 image collection were relatively similar. For the bank height estimation, a 2 m resolution LiDAR-derived DEM (ISU, 2009) was used that was found by Tomer and Van Horn (2018) to have a vertical error of less than one meter when compared to 22 GPS channel transects within the SFIR. The river centerline used by AIMM was obtained via a hydrological analysis of this DEM.

Three hand delineations of each waterway were performed by three separate individuals at a scale of 1:2000. All delineators had substantial previous experience delineating streambank boundaries prior to this analysis. Following the methods of Tomer and Van Horn (2018), delineations of the bank lines were used to create binary channel masks that were then converted to migration rasters of stable land, stable channel, erosion, and deposition that were then paired with AIMM’s volume methodology to estimate erosional and depositional volumes. Because RivMAP does not provide channel masks, the channel masks generated by AIMM were used as input to RivMAP’s migration_masks routine. Also, because RivMAP groups planform migration into three categories (no change, erosion, and deposition) instead of four, the stable channel and stable land categories within AIMM and the delineations were grouped as “no change” for this part of the analysis.

To develop AIMM’s bank height estimation algorithm, several new and existing approaches were compared with streambank profiles derived from a LiDAR DEM. For erosional polygons, the banks heights were estimated as four times the standard deviation of the elevation values within the polygon (AIMM), the range of the elevation values within the polygon (Alternate 1), and the difference between the median elevation value of the land cells and the channel cells within a 3 m buffer of the polygon (Tomer and Van Horn). Methods compared for the depositional polygons included; the difference between the minimum polygon elevation value and median elevation value (AIMM and Tomer and Van Horn), the difference between the minimum polygon elevation value and the mean (Alternate 1), and two times the elevation standard deviation (Alternate 2).

Table 3
Agreement by Reach. Both percent agreement and Cohen’s Kappa increase as stream width increases.

<table>
<thead>
<tr>
<th>Reach</th>
<th>Width (m)</th>
<th>Agreement (%)</th>
<th>Delineated</th>
<th>AIMM</th>
<th>Cohen’s K (%)</th>
<th>Delineated</th>
<th>AIMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>SFIR</td>
<td>17.9</td>
<td>90</td>
<td>81</td>
<td>0.81</td>
<td>0.62</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TC</td>
<td>12.4</td>
<td>87</td>
<td>78</td>
<td>0.77</td>
<td>0.56</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BC</td>
<td>11.5</td>
<td>88</td>
<td>77</td>
<td>0.79</td>
<td>0.52</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 7. Classification by method. Grouped bar graphs displaying the number of pixels classified into each category by AIMM and the three delineations.

The cross-sectional profiles for the comparison were derived from a 100 m transect of a 2 m LiDAR-derived DEM (ISU, 2009). To ensure that bank height estimations were effective within polygons of differing size, the polygonal area of both erosion and deposition polygons was used to divide the polygons into quartiles, and twenty polygons from each quartile were randomly selected for the cross-section analysis. For each polygon, elevation values were extracted from the DEM along a 100 m profile that was placed at the middle of the polygon and perpendicular to the direction of flow. The top and bottom of the erosional and depositional zones were then determined by visual inspection of the profile. Because eroding banks within this region are approximately vertical, the height of the erosional polygons was defined as the range of elevation values within the portion of the profile identified as the eroding bank. Because of the undulating geometries of the depositional zones, the height of the depositional polygons was defined as the difference between the median elevation within the portion of the profile identified as the depositing bank and the elevation of the channel.

3. Results

3.1. Planform comparison

Using a Windows 10 desktop computer with Quad-core 3.70 GHz processors and 16 GB of RAM, the NDWI images were created in 39 min when both images were processed simultaneously. Additionally, for each stream order present within the study area, ten reaches were randomly selected and measured at their beginning, middle, and end. This analysis took 30 min to complete. Once these inputs were created, AIMM took 25 min to complete its analysis of a roughly 23 by 17 km area represented by 3.8 × 10^6 1 m pixels. In total, the AIMM workflow was completed in 1.5 h. For comparison, each set of manual bank delineations took an average of 10 h to complete, and the RivMAP migration_mask routine took approximately the same amount of time as AIMM.

Agreement between AIMM and the delineations was assessed in terms of pixel-wise percent agreement and Cohen’s Kappa. Although some researchers have noted issues with Cohen’s Kappa (Cicchetti and
Feinstein and Feinstien, 1990; Feinstein and Cicchetti, 1990), it is reported here because of its prevalence in other inter-operator reliability studies. The agreement for each unique combination of delineated bank lines and AIMM is reported in Table 2. Overall, average percent agreement between AIMM and hand delineations was 79% and the average Kappa score was 0.58. Similarly, average percent agreement among the delineations was 88%, and the average Kappa score was 0.79. AIMM had the highest agreement within the main branch of SFIR, followed by Beaver Creek and then by Tipton Creek. This trend is likely caused by the increase in average width as you progress from Tipton Creek to SFIR, which reduces the influence of overhanging vegetation cover blocking the channel from view (Table 3). Variations in the total proportion of each category are presented in Fig. 7. Overall, AIMM’s migration map predicted more erosion and less deposition than hand delineations. Once again, agreement between AIMM and delineations was highest in the SFIR.

To compare the migration maps of AIMM and delineations to the migration map of RivMAP, it was necessary to combine the stable land and stable channel classification into one category, because RivMAP reports its results in terms of erosion, deposition, and no change. The percent agreement and Cohen’s Kappa for each combination of delineator and model are shown in Table 4. Overall, both AIMM and RivMAP had high percent agreement, but low Kappa scores when compared to the delineations. In fact, the combination of the stable land and stable channel categories appeared to have a large impact on all Kappa scores, reducing the average Kappa score for the delineations by 0.23, and for AIMM by 0.26. AIMM and RivMAP, however, had high levels of agreement with a percent agreement of 98% and a Kappa score of 0.90, suggesting that AIMM and RivMAP produce migration maps of similar quality.

### 3.2. Bank height comparison

The accuracy of the erosional and depositional bank height methodologies was assessed in terms of the root mean square error (RMSE) and the mean height difference between the transect analysis and the height estimation methodologies (Table 5). Overall, mean bank height derived from the transect analysis was 1.81 m for erosional zones and 0.51 m for depositional zones. For erosional banks, the AIMM method, multiplying the standard deviation of the elevation values within the polygon by four, was found to be the most accurate method for computing bank height with an RMSE of 0.65 m and a mean difference of 0.12 m. Using the range of elevation values (Alternate 1) resulted in a higher RMSE and a larger overestimation of bank height. In contrast, using the Tomer and Van Horn method, the difference between surrounding land and channel heights, resulted in a considerable underestimation of bank height (RMSE of 1.05 m and mean difference of $-0.65$ m). This underestimation is likely caused by slight misalignments between the DEM and the migration map because of channel movement, which in turn led to inclusion of land elevations in the channel median, and channel elevations in the land median.

Overall, using the difference between the median elevation value and the minimum elevation, the AIMM and the Tomer and Van Horn method, was shown to be the most accurate method for estimating depositional bank height with a RMSE of 0.41 m and a mean difference of $-0.01$ m. The difference between the mean and minimum (Alternate 1) was also relatively accurate, but the larger influence of outlying values, in comparison with using the median, caused this method to overestimate bank height. Multiplying the standard deviation of polygon’s elevation values (Alternate 2) on the other hand, had both a larger RMSE and mean difference than either of the other two methods.

### 3.3. Volume estimation

On average, hand delineations estimated a total net volume loss of 477,472 m$^3$ with a standard error of 33,940 m$^3$ (Fig. 8). Meanwhile AIMM estimated a total net volume loss of 476,303 m$^3$. It is worth noting that although AIMM estimated more erosional and fewer depositional

![Fig. 8. Volume estimation. Net volume estimation of each method within each stream and in total. AIMM's predicted volume loss for all reaches is within one standard deviation of the delineations' estimate.](image-url)
pixels, AIMM’s predicted volume loss is within one standard deviation of the delineations. This suggests that our inclusion of a bank height estimate improves the agreement between AIMM the delineations.

4. Discussion

Overall, we found that classifications sourced from channel hand-delineations agreed with each other 88% of the time, whereas AIMM agreed with the delineations 79% of the time. The average Kappa score between AIMM and the delineations (0.58) also indicates that there is a high level of agreement between the delineations and AIMM, even when the increase in accuracy associated with random agreement is considered. Additionally, AIMM and RivMAP were shown to produce consistent results, with an agreement of 98% and a Kappa of 0.90. When using the same bank height estimation methodology and filtering process used by Tomer and Van Horn (2018), we found that AIMM and our delineations produced net sediment volume losses that were consistent with their results. The vast difference in estimated net volume loss between the two methods of height estimations, however, indicates that this approach is sensitive to changes in height methodology, and that Tomer and Van Horn’s estimate of net sediment is likely an underestimate. Overall, these results show that AIMM is an effective tool for monitoring channel migration that produces results comparable to channel delineation methods while also being faster, more consistent, and reproducible.

Although AIMM is an improvement over existing approaches, the results it produces still contain errors. Even so, careful selection of appropriate input data can diminish the impact of error on the analysis. The main sources of error for the planform analysis are derived from image misregistration, changes in wetted area of the channel, and the obstruction of the river channel by vegetation. Other studies (Mount et al., 2003; Rowland et al., 2016) have noted that error from image misregistration and variations in wetted area can dominate the migration signal if river migration is not substantial. Thus, we recommend that images be selected that display migration rates greater than the spatial resolution of the input images, which can be accomplished by selecting imagery with a larger time delta, and that the images that observe the channel under similar flow conditions be used for the analysis. Some have proposed using channel masks that include areas of bare earth as part of the channel to diminish the error associated with wetted area (Rowland et al., 2016), but appropriate bare earth indices for RGB images will need to be developed before this technique can be used at the spatial resolutions of less than 10 m. For areas dominated by deciduous vegetation, it is also recommended that imagery from leaf-off periods be used where available, if doing so does not introduce differences in river stage. For the bank height analysis, the main sources of error are derived from misregistration of the DEM and imagery, and differences in actual channel position caused by river migration. As shown in the results, using the full zones of erosion and deposition to estimate bank height allow for some misalignment between the river channel in the imagery and the DEM. To ensure accurate results, however, the date of the DEM must be bounded by the dates of imagery, otherwise the differences in elevation that allow for the estimation of bank height will fall outside of the depositional and erosional regions. These factors are important to consider, but it is worth noting that the error sources described above are present within any river analysis that utilizes multiple imagery sets and are not unique to AIMM.

If these sources of error are minimized, the remaining error associated with AIMM is likely to be random rather than systematic. This suggests that the negative and positive errors are likely to balance out as the analysis area is expanded, leading to unbiased—albeit noisy—results. We see this effect in our volume analysis, where we found that our overall error decreased when all three streams are considered together. Moreover, although this study’s results show that there is only an 88% agreement rate among hand delineations, successive runs of AIMM have 100% agreement if the same imagery and classification thresholds are used, greatly enhancing the reproducibility of the analysis. Finally, a key reason that AIMM’s performance improved when volume was incorporated is that zones of erosion and deposition that are erroneously identified in the floodplain tend to have very low variance in their elevation values when compared to true zones of erosion, leading to an estimation of bank height near zero. Thus, zones of true erosion are amplified, and zones of false erosion are dampened in the volume calculation. The same is true for depositional zones.

5. Conclusions

Increased sediment and sediment-associated contaminant inputs to rivers and streams are a serious environmental issue that has a multitude of impacts on aquatic life and human infrastructure. Currently, many researchers believe that excess bank erosion is an important component of this issue, but the magnitude of bank erosion in watershed sediment budgets is still poorly documented. Several methods have been developed to estimate sediment flux associated with bank erosion, but the majority of them are either only feasible within watersheds less than 100 km², or use remote sensing data that does not have the resolution needed to detect channel migration within lower order channels. In this study we described AIMM, a channel migration model that is designed to make full use of the high-resolution data found within aerial imagery and compared its results with the those from three hand delineations. For the three stream reaches included in Tomer and Van Horn (2018) we found that when compared to hand delineation estimates, AIMM had inter-operator agreement scores that were, on average, just 7% less than inter-operator agreement scores found between hand delineations, and had 98% pixel agreement with the RivMAP river planform model. Additionally, in terms of area, we found that although AIMM overestimated erosion when computed in terms of area, it performed well when predicting the net volume loss caused by bank erosion.

Overall, AIMM is an effective model for assessing the impact of channel migration on the sediment budgets of second order and larger waterways. As the resolution of aerial imagery increases, models such as AIMM that combine accuracy with computational efficiency will be an important tool for unlocking the scientific and monitoring potential of high-resolution remote sensing data and will serve as an important tool for prioritizing conservation efforts.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References


