River bank erosion and lateral accretion linked to hydrograph recession and flood duration in a mountainous snowmelt-dominated system

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Abstract

Observed and projected global changes in the magnitude and frequency of river flows have potential to alter sediment dynamics in rivers, but the direction of these changes is uncertain. Linking changes in bank erosion and floodplain deposition to hydrology is necessary to understand how rivers will adjust to changes in hydrologic flow regime induced by increasing societal pressures and increased variability of climatic conditions. We present analysis based on aerial imagery, an aerial lidar dataset, intensive field surveys, and spatial analysis to quantify bank erosion, lateral accretion, floodplain overbank deposition, and a floodplain sediment budget in an 11-km long study segment of the meandering East River, Colorado, USA, over 60 years. Assuming steady state conditions over the study period, our measurements of erosion and lateral accretion close the sediment budget for a smaller 2-km long intensive study reach. We analyzed channel morphometry and snowmelt-dominated annual hydrologic indices in this mountainous system to identify factors influencing erosion and deposition in nine study sub-reaches. Results indicate channel sinuosity is an important predictor for both lateral erosion and accretion. Examination of only hydrologic indices across the study segment regardless of sub-reach morphology, indicate that the duration of flow exceeding baseflow and the slope of the annual recession limb explain 59% and 91% of the variability in lateral accretion and erosion, respectively. This work provides insight into hydrologic indices likely to influence erosion and sedimentation of rivers and reservoirs under a shifting climate and hydrologic flow regimes in snowmelt-dominated systems.

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Key Points:

- Floodplain erosion and accretion estimated over 60 years using aerial lidar, repeat aerial imagery, field surveys, and historic flow data
- Hydrograph recession and duration of floodplain inundation explain 91% and 59% of the variability in bank erosion and lateral accretion
- Results can inform potential response to shifting climatic conditions and hydrologic regimes of snowmelt-dominated rivers

Abstract

Observed and projected global changes in the magnitude and frequency of river flows have potential to alter sediment dynamics in rivers, but the direction of these changes is uncertain. Linking changes in bank erosion and floodplain deposition to hydrology is necessary to understand how rivers will adjust to changes in hydrologic flow regime induced by increasing societal pressures and increased variability of climatic conditions. We present analysis based on aerial imagery, an aerial lidar dataset, intensive field surveys, and spatial analysis to quantify bank erosion, lateral accretion, floodplain overbank deposition, and a floodplain sediment budget in an 11-km long study segment of the meandering East River, Colorado, USA, over 60 years. Assuming steady state conditions over the study period, our measurements of erosion and lateral accretion close the sediment budget for a smaller 2-km long intensive study reach. We analyzed channel morphometry and snowmelt-dominated annual hydrologic indices in this mountainous system to identify factors influencing erosion and deposition in nine study sub-reaches. Results indicate channel sinuosity is an important predictor for both lateral erosion and accretion. Examination of only hydrologic indices across the study segment regardless of sub-reach morphology, indicate that the duration of flow exceeding baseflow and the slope of the annual recession limb explain 59% and 91% of the variability in lateral accretion and erosion, respectively. This work provides insight into hydrologic indices likely to influence erosion and sedimentation of rivers and reservoirs under a shifting climate and hydrologic flow regimes in snowmelt-dominated systems.

Plain Language Summary

Changing climatic conditions are poised to alter the timing and magnitude of precipitation, snowpack, snowmelt and the balance of water and sediment within river corridors. Understanding how these changes affect the stability of land along rivers is important for securing infrastructure, maintaining healthy ecosystems, preserving water quality, and understanding the fate and transport of contaminated sediment. This research uses aerial imagery, laser topographic scanning technology, field measurements of water and soil, and historical river flow data to examine linkages between river flows and erosion and deposition of sediment along the floodplain of a mountain over 60 years. Results show that river bank erosion is linked to the rate at which the river flows decrease following snowmelt-driven peaks and that the amount of sediment that is deposited along the river banks is linked to the duration of flooding; both are influenced by channel sinuosity. These results have important implications for understanding how rivers and freshwater resources may be impacted by shifting climatic conditions and hydrologic regimes.

1 Introduction

A large number of studies have quantified long-term channel migration and episodic bank erosion, but these approaches do not fully examine the link between changes in river flows and the timing of river bank erosion, particularly in snowmelt-dominated systems. Rapid changes in river flows likely strongly influence river bank stability and erosion on seasonal scales (Wolman, 1959; Simon et al., 2002). Annual hydrologic trends including the magnitude, frequency, timing, duration, and rate of change in discharge are important aspects of river flow regimes that influence aquatic and riparian habitat (Poff et al., 1997) and sediment dynamics including erosion and deposition along floodplains (Wohl et al., 2015). More specific investigation of hydrologic flow regimes have been examined using various hydrologic indices to provide insight into riverine ecosystems (Richter et al., 1996) and germination of riparian vegetation (Benjankar et al., 2014; Caponi et al., 2019). These changes that characterize annual hydrologic flow regimes across all climatic zones can include very rapid changes in discharge, such as those in flashy rainfall dominated systems. Alteration of natural flow regimes induced by dams and flow regulation – common in snowmelt dominated systems – can mimic these rapid changes and greatly alter sediment regimes and riverine habitat (Richter et al., 1996; Poff et al., 1997; Lenhart et al., 2013).

While understanding the mechanisms and timing of bank erosion is fundamental to landscape evolution and risk to infrastructure, it is also crucial for nutrient and carbon dynamics and potential impact to water resources. The rate at which banks erode and rivers migrate substantially influence nutrient and carbon dynamics (Sekely et al., 2002; Sutfin et al., 2016), ecosystem habitat (Naiman et al., 2010), and the fate and transport of contaminants bound to floodplain sediment (Macklin et al., 2006; Rhoades et al., 2009). Changes in erosion and deposition along floodplains can greatly alter carbon storage along floodplains (Noe & Hupp, 2005; Hoffmann et al., 2009; Omengo et al., 2018; Scott & Wohl, 2018; Lininger et al., 2019), which is substantially higher within snowmelt-dominated mountainous headwater systems (Wohl et al., 2012; Sutfin et al., 2016; Sutfin & Wohl, 2017). Contaminants adsorbed to mineral facies and organic matter in floodplain and bank sediment of mountain streams, such as the heavy metals from the mining spill along the Animas River in Colorado, USA, (Rodriguez-Freire et al., 2016), are susceptible to erosion and pose a risk for downstream water quality and ecosystems. The research presented here is motivated by our efforts to quantify carbon storage and dynamics in a mountainous region along the floodplain of the East River near Crested Butte, Colorado, USA. The general goals of this research were to quantify erosion and deposition along the East River and to link these observations to past hydrologic conditions.

Many researchers have used remotely sensed imagery to examine bank erosion and lateral accretion over years to decades (James E. Pizzuto, 1994; Micheli & Kirchner, 2002a, 2002b; S. S. Day et al., 2013b, 2013a; Lenhart et al., 2013; Rowland et al., 2016; Schook et al., 2017; Schwenk et al., 2017; Caponi et al., 2019). Using these data as a basis for understanding river migration rates, modeling efforts seek to understand the physically-based drivers of channel migration over long time scales (i.e., 10^2 to 10^5 years) (Howard, 1996; Güneralp & Rhoads, 2009; G. Parker et al., 2011; Bogoni et al., 2017), or use near-bank velocities to estimate bank erosion over shorter time scales (Darby et al., 2007; Gary Parker et al., 1982; J. E. Pizzuto & Meckelnburg, 1989).

Physically based models of bank erosion provide understanding of cantilever failures, slip or rotational failures, and planar shear resulting from undercutting, positive pore pressure, and excess bank shear stress, respectively (Thorne & Tovey, 1981; Simon et al., 2000; Langendoen & Simon, 2008; Langendoen & Alonso, 2008). Available models tend to use bankfull flow conditions to model bank erosion (Langendoen & Alonso, 2008) and past work indicates that more erosion is likely to occur at high flow conditions. However, changes in flow have also been identified as potential drivers for bank failure because positive pore pressure of saturated banks combined with the loss of supporting pressure when stage declines make slip and rotational bank failures likely (Rinaldi & Casagli, 1999). Thus, additional hydrologic indices such as the rate of change offer the potential to provide a more robust understanding of the hydrologic drivers of bank erosion.

Effectively linking floodplain erosion and accretion to hydrology requires the assumption of minimal changes in sediment supply and are simplified by the assumption of steady state and a balanced sediment budget over the time period examined. Sediment budgets at the watershed scale must consider the production of sediment from weathering and erosion, elements of storage within the basin, sediment transport processes, and the resulting sediment yield (Dietrich et al., 1982; Gellis & Walling, 2013). Sediment budgets for only floodplains, however, may be simplified needing only to account for the time averaged balance of erosion and deposition along the floodplain alone (Reid & Dunne, 2016). Examples of floodplain sediment accounting includes those in the southwestern United States by Gellis et al. (2012) and in the Le Sueur watershed in Minnesota, USA, by Belmont et al., (2011) and Day et al., (2013). Here, we use a floodplain sediment budget to constrain estimates of floodplain erosion and sedimentation along a subalpine meandering river using a combination of field observations, remotely sensed imagery and lidar, and GIS spatial analysis.

We studied the connections between hydrology and sediment flux of the East River floodplain, using (1) repeat aerial imagery to quantify lateral erosion and accretion over a 60-year period, (2) measurement of floodplain fine sediment depth, (3) an aerial lidar digital elevation model (DEM) and (4) empirical relationships with characteristics of the flow regime to identify hydrologic drivers of river bank erosion and lateral accretion. From this work, we developed an empirical relationship between hydrology and sediment fluxes on decadal time scales to address the primary goal to determine what morphometric variables (e.g., sinuosity, channel slope, width) and hydrologic indices (e.g., peak magnitude, timing of peak, slope of the recession limb) best explain observed floodplain erosion and accretion on the snowmelt-dominated East River. We also calculated a sediment budget to verify our accounting of eroded and accreted floodplain sediment and used the results to examine a practical and cost-effective way to estimate hydrologic influence on floodplain erosion and accretion that does not require the intensive fieldwork and lidar analysis employed in this study.

2 Study Area

We studied an 11-km long segment of the East River approximately 3.5 km down valley from Gothic, CO, (Figure 1) near Crested Butte. At the downstream end of the study segment, the East River drains approximately 134 km^2 and has an annual average precipitation of 64 cm (SNOTEL, 2017). The floodplain lies directly downstream of steep, confined, mountainous tributaries that incise through sandstones, mudstones, shales, granodiorite and metamorphosed byproducts of the uplifted White Rock pluton in the Elk Mountains of Colorado (Gaskill et al., 1991). Within the floodplain reach, the East River is a gravel-cobble bed, sinuous alluvial river approximately 20-m wide on average and bounded by lateral Pinedale glacial moraines, landslide deposits, and outcrops of Mancos Shale along the bed and valley walls. Sedges, grasses, and willows dominate the vegetation along the floodplain with isolated trees, dominantly blue spruce, scattered along the reach, but rarely located along the river banks. Throughout the floodplain, extensive beaver activity results in dams, lodges and the introduction of large wood from the surrounding hillslopes. Floodplain fine overbank sediment is dominated by silt-size particles with varying proportions of sand, clay, and minimal gravel content (Malenda et al., 2019). Beneath fine sediment, the floodplain is composed of gravel and cobbles, and contains lenses of finer, sorted material. Erosion of underlying gravels and undercutting of fine overbank sediment commonly result in cantilever failure of grass-covered blocks along the East River 11-km long study segment (Figure 1D, S1).

The East River is a typical snowmelt-dominated system, which is characterized by a gradual rising limb as temperatures warm and snow melts in the spring months of

April and May. An annual peak flow commonly occurs in the latter half of May or early half of June after peak snowmelt, followed by a gradual recession limb that takes place over weeks to months at which discharge returns to some baseflow condition sometime between September and November.

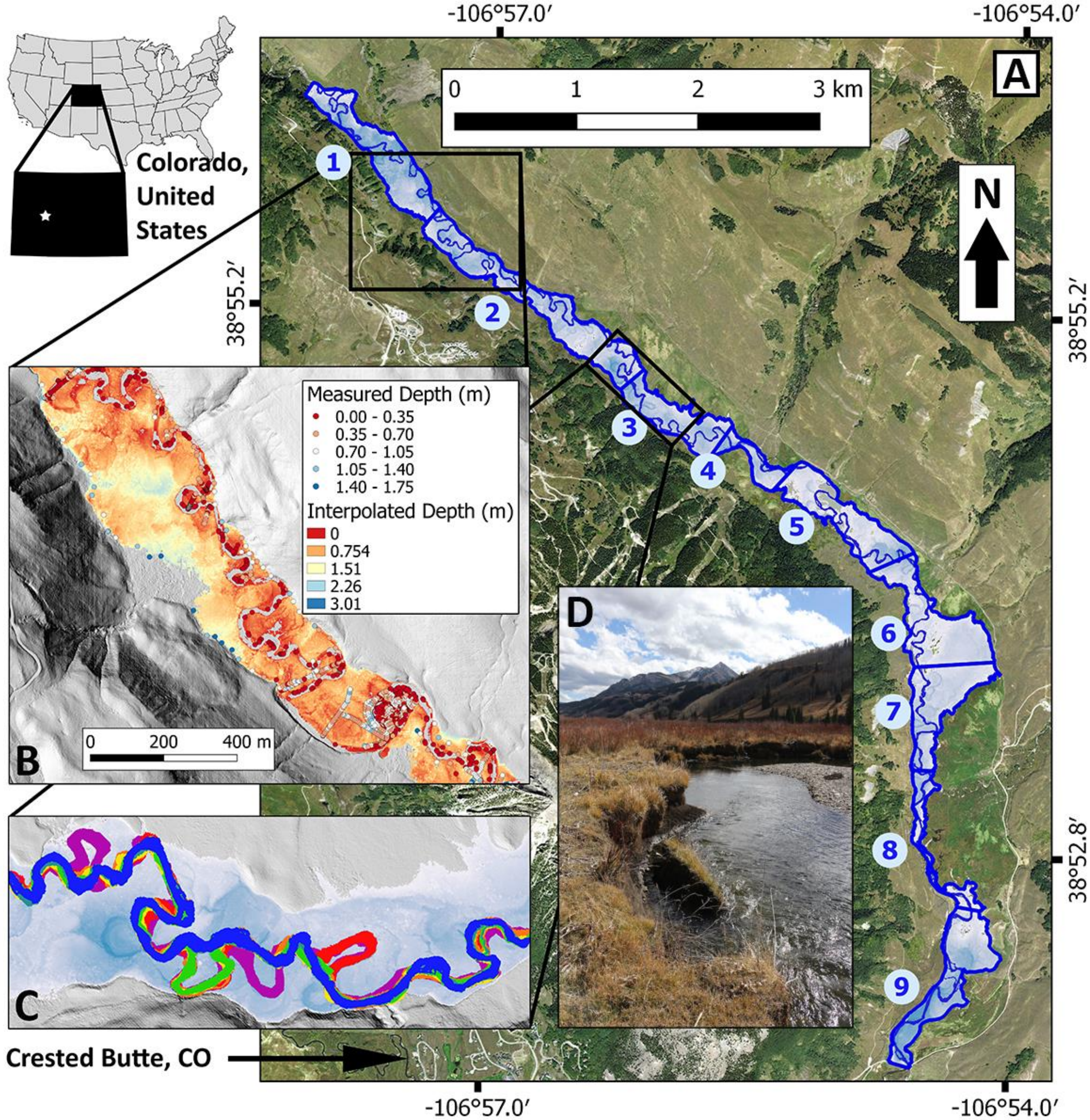

Figure 1. Map of study area on the East River near Crested Butte, Colorado, USA. The floodplain was delineated by “flooding” a 0.5-m resolution lidar digital elevation model along the 11-km long study segment, which was divided into 9 study reaches (A) based on changes in valley slope. The depth of fine sediment was measured across the floodplain at 1847 points and interpolated across the upper 2 km, intensive study reach

(B) consisting of reach 1 and approximately half of reach 2, ending at the downstream extent of the black box in (A). Masks of the river channel, depicted in various colors, were derived for all seven time periods (C), and used to determine lateral accretion and erosion, typically occurring as cantilever failures in the study area (D). Shades of blue indicate relative depth of water across the delineated floodplain in A and C.

Limited land-use impacts have influenced the watershed upstream of the 11-km long study segment of the East River. From 1880 to 1890, a silver mine operated along Copper Creek upstream of Gothic, CO, the present location of the Rocky Mountain Biological Laboratory. The mining area is now designated as US Forest Service (USFS) national forest and wilderness area. Land use along the 11-km long study segment consists of small privately owned parcels and U.S. Forest Service (USFS) land, on which ranchers graze cattle for limited portions of the year (Theobald et al., 1996). Limited property access restricted our field investigations to the upper 2 km, intensive study reach (Figure 1A; Reach 1 and half of reach 2). Although flow diversions exist within the 11-km long study segment, they were present prior to beginning of the study period in 1955 and they primarily capture runoff from tributaries before they reach the East River.

3 Materials and Methods

Spatial analysis of aerial lidar, repeat aerial imagery, surface water flow measurements and historical hydrologic flow analysis, measurements of floodplain fine sediment depth, and multiple linear regression were used to examine linkages between hydrology and bank erosion, accretion, and channel migration rates over 60 years.

3.1 Terrain Analysis and Study Reach Delineation

Aerial lidar was collected in August of 2015 for the entire East River watershed. Average bare-ground point cloud density of lidar was 4.29 points/m^2 resulting in a total accuracy with root mean squared error of 0.05 m at the 95% confidence level. A hydro-flattened, bare-ground DEM with a horizontal resolution of 0.5 m derived from the lidar point cloud data was used for all topographic analysis. Using the valley slope, we divided the ~11-km long floodplain segment into nine study reaches. We calculated the valley slope using a best-fit line of elevation points extracted from the 2015 DEM and spaced every 10 meters down the valley center. We detrended the slope of the 9 sub-reaches using the raster calculator in QGIS and recombined them to generate a floodplain DEM with zero down-valley slope and a maximum total relief of 5.44 m. We artificially entrenched the flat lidar water surface by 2 meters and used the *r.fill.dir* Grass tool in QGIS to flood the detrended DEM at a depth of six meters to delineate the approximate extent of the floodplain. We verified the digitally delineated floodplain extent with field observations of distinct breaks in slope, such as the base of lateral moraines, toes of alluvial fans, and abutments to incised bedrock outcrops.

3.2 Channel Position and Movement using Aerial Imagery

We used aerial images from seven dates (i.e., 1955, 1973, 1983, 1990, 2001, 2012, 2015) obtained from the US Geological Survey, US Department of Agriculture, and the US Forest Service to delineate the channel, measure channel widths, sinuosity, and lateral erosion and accretion over time. All imagery was resampled to 1-m resolution to allow direct comparison between images. We georeferenced the 2015 imagery using the 2015 lidar DEM dataset as a reference using >6 control points including the corners of buildings, intersections of roads and fences, and the base of mature trees. All other images were georeferenced (if not already done so by the source agency) through comparison with similar point types in the 2015 georeferenced image.

To analyze channel characteristics and compare changes over time, we generated binary channel masks for each set of aerial imagery. For color imagery between 1973 and 2015, we generated masks of bankfull river extent using red-green-blue (RGB) color bands and the normalized difference water index (NDWI) to classify the channel water surface in each image (Figure 1C; McFeeters, 1996) using the object-oriented classification software, eCognition. To control for variations in water levels between images, regions of tan and grey gravel and sand bars devoid of vegetation and exposed, un-vegetated bank faces were included in the channel mask as an estimate of bankfull extent (Gurnell, 1997; Richard et al., 2005; Mount & Louis, 2005; Fisher et al., 2013; Rowland et al., 2016; Donovan et al., 2019). The black and white 1955 USDA photos required manual delineation of the channel mask.

Metrics calculated to quantify the channel and floodplain attributes for the nine valley reaches and entire 11-km long study segment included: valley, floodplain, and channel areas; valley and channel lengths; elevation change along the reach; valley and channel slopes; sinuosity; average channel width; and valley confinement. The channel area relative to the area of delineated valley floor defined valley confinement as a proxy for potential of the floodplain to accommodate channel migration, dissipate energy during overbank flow, and facilitate overbank deposition. Channel sinuosity measures the channel length divided by the straight down-valley length. Channel slope was calculated as the valley slope divided by channel sinuosity. Channel width, linear erosion, and accretion rates were determined for each bank pixel using the Spatially Continuous Riverbank Erosion and Accretion Measurements algorithm (SCREAM; Rowland et al., 2016).

Linear rates represent the distance that a river bank face moves in a given time interval by measuring the Euclidean distance between a bank pixel in one river mask and the closest bank pixel at the subsequent river mask. Eroded and accreted floodplain areas derived from SCREAM were divided by the number of years within that time period and the channel length to estimate linear rates of erosion and accretion. Three sources of error are associated with our measurements of linear change: image registration, image classification and the accuracy of SCREAM output (Rowland et al., 2016). Average estimated registration error for the 1-m imagery from 1973 to 2015 was 0.58 m. Poor image quality of the 1955 photographs prevented direct estimates of error using this method, so we have assigned a registration error equal to two times the highest error (1.2 m) in areas for the period between 1955-1973. Errors associated with area-based erosion and accretion measurements as a result of image mis-registration for each time period were assigned as percentage of change in areas following the methodology detailed in Rowland et al. (2016). Total measurement errors were estimated by combining registration, classification, and methodological errors in quadrature (Rowland et al. 2016)) (Table S1).

3.3 Vertical Accretion Rates

We estimated long-term vertical accretion rates using a combination of field-based measurements of fine-grained deposit thickness and changes in channel position from aerial imagery between 1973 and 2015. Images from 1955 were excluded from this analysis because of the uncertainty associated with the poor-quality images. In 2016, along the upper 2 km, intensive study reach (Figure 1A, reach 1 and half of reach 2), we measured thickness of fine-grained deposits at 324 locations on 21 transects by inserting a soil probe into the floodplain surface until refusal at bedrock or gravel-size material (>2mm). Mean migration rate was estimated from SCREAM output and the distance to each transect point from the channel was converted into duration since channel occupation by dividing by the bend averaged migration rate (Figure S2). More detailed analysis to examine vertical accretion rates in conjunction with the channel migration rate over each time period was conducted and outlined in the supplemental information (Figure S2), but suspected point bar erosion did not produce robust results that support continuous vertical accretion for each time period. Instead, we used the total depth to represent an average deposition rate over the time period examined. The measured depth of fine sediment (d_i) was then divided by the duration since occupation by the river channel (t_i, when fine sediment depth would have been equal to zero) to estimate a mean vertical accretion rate (a_i; Equation 1).

$$\overline{a_i} = \frac{d_i}{t_i} \quad (1)$$

Potential predictors of floodplain vertical accretion rates, across the upper 2 km, intensive study reach were assessed through stepwise multiple linear regression. Variables examined for this analysis were similar to those described above, with the following additions. Distance from the channel was measured in the field. Relative elevation from the bankfull stage at the transect was extracted from the lidar at the top of point bars were bar sand/gravel transitioned into vegetation cover. Along each transect, channel width, valley width, and the ratio between the two (valley confinement) were measured from the imagery in GIS. Localized valley slope, channel slope, and sinuosity were measured using GIS extending approximately 50 m upstream to 50 m downstream of the transect. Mean values of radius of curvature, lateral accretion rate, and erosion rate were calculated along each meander bend. Measurements were denoted as either being on the inside or outside of a bend. The angle of each transect was used as a proxy for the angle of each river bend relative to the down valley direction from 0-90º.

3.4 Estimating floodplain sediment volumes

Areas of accretion and deposition from the SCREAM analysis were converted to sediment volumes using measured sediment depths. In our analysis, we only estimate volumes of fine grained (less ~ 2mm in grain diameter) sediments deposited on top of the gravel-rich channel and point bar deposits. In addition to the soil probe measurements collected on point bar transects (Section 3.3), 1,587 measurements were made along the upper 2 km intensive study reach (Figure 1A, Reaches 1 and 2; Sutfin & Rowland, 2019). We subtracted these depth measurements from the DEM elevations using the *raster calculator* in QGIS to calculate an absolute elevation of underlying gravel/bedrock. We then generated a triangular irregular network (TIN) of the gravel/bedrock surface elevation using the *interpolate* tool in QGIS. By subtracting elevations of this interpolated surface from the ground surface elevations, we created a spatially continuous isopach map of fine-grained floodplain sediment.

This interpolated fine-sediment map represents conditions in 2015. At the location of the current channel the fine sediment has values of zero, as such, areas of historical floodplain erosion that intersected the 2015 channel did not have accurate values of the floodplain volume eroded. To correct for this error we interpolated 2015 fine-sediment thickness across the channel using a 3 m buffer that extended beyond the locally thin deposits covering active point bars. We used the *close gap* Saga tool in QGIS (threshold = 0.1) to create the corrected isopach map. We calculated eroded volumes by multiplying the areas of eroded regions derived from the aerial imagery for each time interval by the interpolated isopach map of fine sediment within those mapped areas.

Using the estimated vertical accretion rates from our soil probe transects we estimated an average deposition rate for laterally accreted regions along the channel and developed a multiple linear regression model to estimate overbank deposition on the stable floodplain surface in response to floods. For the laterally accreted areas, we used the average migration rates at the bends determined using the probe transects described above in section 3.3 to determine the portion of contemporary floodplain that would have been formed by lateral accretion during the 42 years between 1973 and 2015. A reach-based average migration rate and resulting mean migration distance along the probe transects were used to estimate an average vertical accretion rate from all points within the mean migration distance for the entire period between 1973-2015 (Table S2). This average rate was multiplied by the mapped accretion areas from the aerial photos and SCREAM output to provide a volume of laterally accreted sediments.

Overbank deposition rates beyond 10 m were calculated for each cell utilizing another multiple linear regression model including only the two strongest predictor variables, distance from the channel and relative elevation from the channel (Figure S3). The *proximity grid* Saga tool in QGIS was used to create a grid based on distance from the channel for images from the six years. Floodplain elevation relative to the channel was calculated by subtracting the minimum elevation from the detrended 2015 DEM floodplain surface (derivation described above in section 3.1). This assigned a relative elevation to every raster pixel. The river channel buffered by three meters on both sides was subtracted from the relative elevation grid and the *close gap* tool in QGIS was used to interpolate elevations across the channel.

The distance-from-channel raster and the detrended-valley DEM were used as input to the vertical accretion rate regression model equation in the raster calculator to generate raster grids of estimated overbank deposition rates for all six time periods. Overbank sediment deposition estimates of volume were made by multiplying calculated rates by the number of years in the respective time interval, summing all pixel values for each period, and multiply that value by the area of each pixel (0.25 m^2). Vertical accretion within abandoned channels was estimated using the lateral accretion rate of 3.3 cm y^{-1} within the first 10 m from the channel for periods following cutoff occurrence. Aggradation of previously abandoned channels was based on the relative vertical and horizontal distance from the active bankfull channel at distances exceeding 10 m. Rates of volume of sediment accreted and eroded during each time period were estimated by dividing the total volume of sediment by the number of years in each time period.

3.5 Streamflow Data and Hydrologic Analysis

Streamflow was measured 22 times near the Crested Butte city water pump house in the upper 2 km, intensive study reach, from October, 1st, 2014, to September, 30th, 2017, and a stage-discharge rating curve was created against stage data recorded every 15 minutes ($r^2 = 0.99$) (Carroll & Williams, 2019). To extend the flow record prior to 2014, we regressed measured discharge at the 2-km intensive study reach against data from the US Geological Survey stream gage on the East River at Almont (gage # 09112500) 40 km downstream ($r^2 = 0.97$; Figure 3A). Using this regression, we generated a synthetic hydrograph for the study site from 1934-2018 using the Almont streamflow data (Table S3). A comparison of the synthetic hydrograph and flows measured between 2014 and 2018 showed a strong agreement with a Nash-Sutcliffe Efficiency coefficient (NSE) of 0.97 (Figure 3B). Flow frequency analysis was conducted on the entire synthetic hydrograph to determine annual statistics for the continuous 82 years. Analysis of possible hydrological drivers for erosion and deposition examined the synthetic hydrograph from 1955 to 2015 to correspond with the aerial imagery analysis.

We used R software (R Core Team, 2017) to extract synthetic hydrograph characteristic between 1955 and 2015. An average minimum flow value of 0.49 $m^3 s^{-1}$ during the low-flow months of October, November, December, January, February, and March were used as a reference baseflow condition. Bankfull flow was estimated as 8 m^3 s-1 based on field observations and hydrologic analysis indicates an approximate recurrence interval of 1.2 years. The mean value for the day of the year on which peak flow occurred, the last day exceeding bankfull flow conditions, and the last day exceeding baseflow conditions were calculated for each time period. The maximum and mean values within each time period were calculated for annual hydrograph peak magnitude, peak timing, annual volume of discharge, the annual volume of water above bankfull flow, duration between the first and last day of flow exceeding baseflow, the number of days on which baseflow occurred, the annual volume of discharge exceeding bankfull, duration between the first and last day of flow exceeding bankfull flow, the number of days on which bankfull flow occurred, and the cumulative number of days since the last bankfull flow, the total recession limb slope from the annual maximum peak to baseflow, the bankfull recession limb slope from bankfull stage to baseflow, and the number of peaks above bankfull flow. Recession slopes were estimated as the slope of the line between peak discharge and the first occurrence of baseflow conditions.

A secondary analysis was conducted to examine diel fluctuations in discharge associated with the slope of the recession limb of each annual hydrograph. A regression analysis of 15-minute streamflow data from the same USGS gauge and measured flow at the study site from 2015-2019 yielded an $r^2 = 0.94$. This regression was used to extend the study site discharge data to span the duration of the 15-minute data from 1988-2019. Maximum and minimum daily values were determined using hourly data and the number and magnitude of diel fluctuations exceeding 6 m^3s^{-1} within a window of 5 to 10 m^3s^{-1} were summed. Correlations were examined between the recession limb slope and the number, the summed magnitude, and the average magnitude of diel fluctuations to occur within the defined recession window.

3.6 Statistical Analyses

The number of potential variables for all multivariate regression models used to identify significant predictors was reduced to minimize collinearity of predictor variables prior to multiple linear regression. Starting with the most strongly correlated variable and working sequentially through variables with decreasing correlation values, variables were eliminated as potential predictors for the regression model if they were moderately cross correlated (r > 0.7) with another more strongly correlated variable (Dormann et al., 2013) already selected as a predictor. Stepwise multiple linear regression was conducted using the *stats* package *lm* function in R statistical software to examine possible predictor variables and determine the best regression model for: (1) the area of accreted and (2) the area of eroded floodplain along nine study reaches, and (3) vertical floodplain deposition rate estimated from measurements of floodplain fine sediment depth along the upper 2 km, intensive study reach over the 6 time periods. Multiple linear regression assumptions of normality and homoscedasticity of model residuals were met with power transformations and verified using the Shapiro-Wilk normality test (*shapiro.test* function) and the non-constant error variance test in R (*ncv.test* function), for which details are provided in supporting material. Variables were included in stepwise multiple linear regression to identify the best regression model based on minimizing the Akaike Information Criteria (AIC).

4. Results

4.1 Channel and floodplain metrics

The floodplain delineation of the entire 11-km long study segment resulted in a valley bottom area of 2.65 km^2 with a total valley length of 10.62 km and a total valley slope of 0.64%. Despite the occurrence of 21 channel chute cutoffs in the 60-year time period, channel slope and the sinuosity for the entire river segment remained relatively constant during the six periods examined. Channel slope along the entire 11-km long study segment varied from 0.34 to 0.36% over the 60-year time period. Sinuosity fluctuated about a mean value of 1.81 ± 0.04 m/m (SD) with a minimum and maximum of 1.77 to 1.89 (Table 1).

Table 1. Morphological characteristics of the entire East River study segment derived from remotely sensed imagery and lidar for each time period. Channel width was calculated as a mean of channel width pixel values from SCREAM and standard deviations of those averages are provided following each mean.

Year	Floodplain area (km^2)	Channel Area (km^2)	Channel Length (km)	Sinuosity (m/m)	Channel slope (%)	Confinement (m^2/m^2)	Mean channel width (m)
1955	2193.6	459.0	20.08	1.89	0.339	0.17	25 ± 2
1973	2254.0	398.7	19.29	1.82	0.353	0.15	20 ± 2
1983	2222.3	430.3	18.80	1.77	0.362	0.16	23 ± 3
1990	2295.4	357.3	18.90	1.78	0.361	0.13	19 ± 3
2001	2275.4	377.3	19.39	1.83	0.352	0.14	21 ± 3
2011	2296.2	356.5	18.81	1.77	0.362	0.13	19 ± 1
2015	2312.2	340.4	18.98	1.79	0.359	0.13	17 ± 1

Table 2. Morphological characteristics of nine study reaches derived from remotely sensed imagery and lidar. Values are averaged from the seven images spanning 60 years and standard deviations of those averages are provided following each mean.

Reach	Valley area (m^2)	Valley Length (m)	Valley slope (%)	Floodplain area (m^2)	Channel Area (m2)	Channel Length (m)	Sinuosity (m/m)	Channel slope (%)	Confinement (m^2/m^2)	Channel width (m)
1	344236	1471	0.94	294462	49774 ± 6292	2860 ± 130	1.94 ± 0.09	0.48 ± 0.02	0.14 ± 0.02	18 ± 3
2	489119	2126	0.74	405784	83334 ± 6234	4735 ± 143	2.23 ± 0.07	0.33 ± 0.01	0.17 ± 0.01	18 ± 2
3	232658	910	0.55	199873	32785 ± 6046	1740 ± 99	1.91 ± 0.11	0.29 ± 0.02	0.14 ± 0.03	19 ± 3
4	93445	595	0.86	76134	17311 ± 1495	903 ± 60	1.52 ± 0.10	0.57 ± 0.04	0.19 ± 0.02	20 ± 2
5	330488	1142	0.68	283494	46994 ± 5334	2419 ± 170	2.12 ± 0.15	0.32 ± 0.02	0.14 ± 0.02	20 ± 2
6	378666	924	0.56	344169	34497 ±4194	1448 ± 248	1.57 ± 0.27	0.37 ± 0.06	0.09 ± 0.01	22 ± 3
7	302210	855	0.33	271371	30839 ± 6166	1490 ± 116	1.74 ± 0.14	0.19 ± 0.02	0.10 ± 0.02	21 ± 3
8	126101	1175	0.54	89108	36992 ± 2469	1583 ± 26	1.35 ± 0.02	0.40 ± 0.01	0.29 ± 0.02	23 ± 3
9	355743	1420	0.46	299779	55965 ± 8114	2001 ± 53	1.41 ± 0.04	0.33 ± 0.01	0.16 ± 0.02	23 ± 4

Valley slope ranged from 0.33% to 0.94% along each of the 9 delineated study reaches with a mean of 0.36 ± 0.19% (SD; Table 2). Mean valley confinement for the time period was 0.16 ± 0.02 m^2/m^2 (mean ± SD). Study reach 8 is the most confined reach (C_v = 0.29 ± 0.02) and is located toward the downstream end of the 11-km long study segment where the tributary alluvial fan from Brush Creek constricts the East River valley. Reach sinuosity (P) averaged over the time period is also lowest in study reach 8 at 1.35 ± 0.02 m/m (Figure 2). The highest reach mean sinuosity (P = 2.23 ± 0.07) occurred in reach 2, which is moderately confined (C_v = 0.17 ± 0.01) (Table 2).

Averaged over all time periods, channel width generally increased from upstream reaches to downstream reaches (Table 2). Although the channel mean width fluctuated with intervals of widening followed by narrowing, there was a net overall decrease over the 60-year time period. The average channel width for the entire 11-km long study segment decreased from a high of 25 ± 2 m in 1955 to a minimum of 17 ± 1 m in 2015. The greatest width reduction (~5 m) occurred between 1955 and 1973, but a substantial decreased of >4 m also occurred during two time periods between 2001 and 2015.

4.2 Channel Migration and Floodplain Area

The net balance between total area of eroded and accreted floodplain by the East River varied over the six time periods, with estimated accretion greater than erosion in four out of six time periods (Table 3). Over the entire 60-year period accretion exceeded erosion by 120,036 **±** 43,973 m^2, equal to 5.3% of the total area of the valley bottom. This accretion total includes the area of 21 abandoned channels arising from meander bend cutoffs. The highest rate of change in floodplain sediment balance occurred from 1983-1990 with a mean accretion rate outpacing erosion by a factor of four (Table 3; Figure 2). There was an observed decrease in channel width during this period, followed by a period dominated by erosion and channel widening. The period between 1973 and 1983 was dominated by the largest erosion rates observed in this study, and was accompanied by an observed increase in channel width (Table 1, 3; Figure 2A).

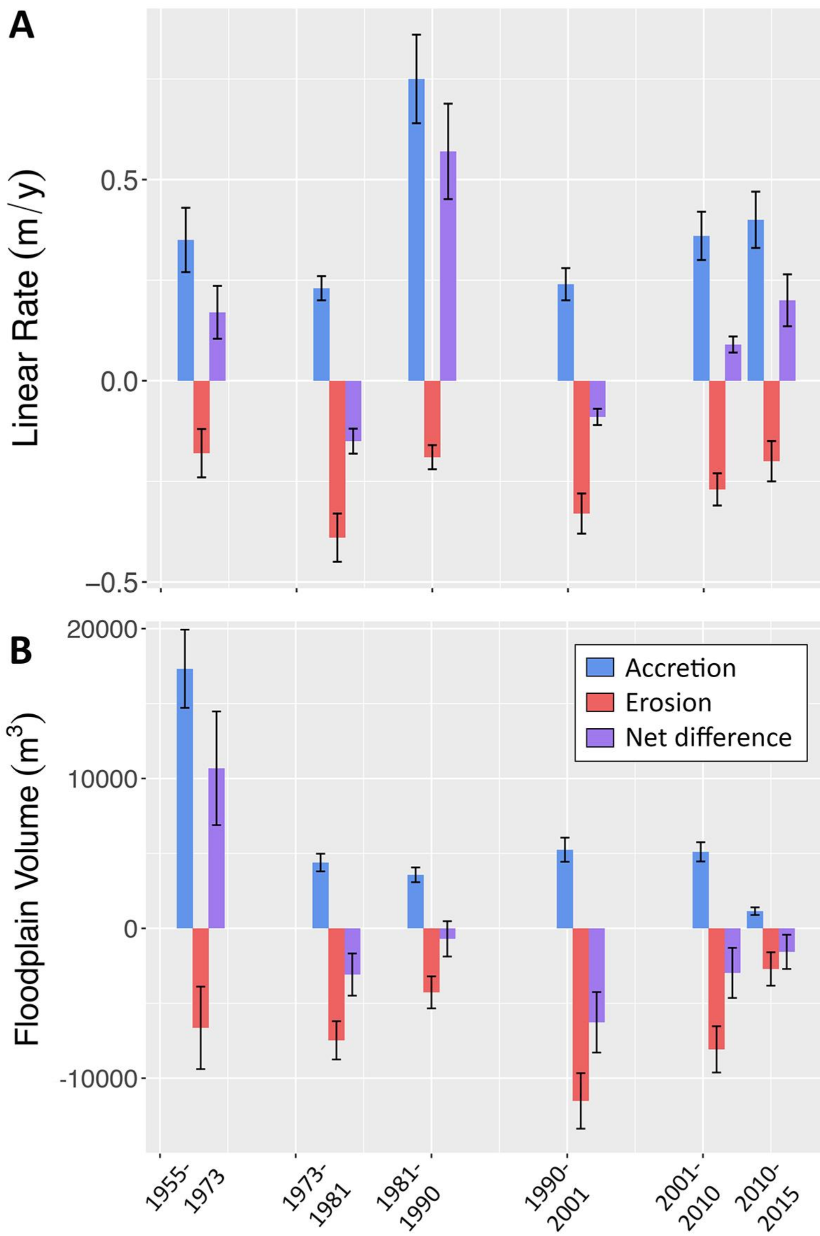

Figure 2 Bar plots of estimated accretion, erosion, and net difference (accretion minus erosion) in linear rates along the entire 11-km long study segment (A) and volume of floodplain fine sediment along the upper 2 km, intensive study reach (B) during each time period examined over the 60 year study period.

Table 3. Area accreted and eroded across the entire 11-km long study segment and hydrologic flow indices on the East River during the six time periods of the study.

	1955-1973	1973-1983	1983-1990	1990-2001	2001-2011	2011-2015	Mean	Total
Duration (years)	18 ± 0.3	10 ± 0.3	7 ± 0.3	11 ± 0.3	10 ± 0.3	4 ± 0.3	10 ± 0.3	60 ± 0.8
Accretion (m^2)	125529 ± 27774	45276 ± 6339	99194 ± 13887	50226 ± 8036	70686 ± 9189	30156 ± 7539	70178 ± 12127	421067 ± 34789
Erosion (m^2)	-64915 ± 25388	-74670 ± 12694	-24569 ± 6142	-69550 ± 11128	-52358 ± 9948	-14969 ± 6137	-50172 ± 11906	-301031 ± 33224
Net Change (m^2)	60614 ± 37629	-29394 ± 14188	74625 ± 15185	-19324 ± 13726	18328 ± 13543	15187 ± 9721	20006 ± 17332	120036 ± 48106
Accretion Rate (m^2y^{-1})	6974 ± 1548	4528 ± 652	14171 ± 2095	4566 ± 744	7069 ± 949	7539 ± 1987	7474 ± 1329	44846 ± 3551
Erosion Rate ($m^2 y^{-1}$)	-3606 ± 1412	-7467 ± 1294	-3510 ± 893	-6323 ± 1030	-5236 ± 1010	-3742 ± 1566	-4981 ± 1201	-29884 ± 2999
Mean linear Accretion Rate ($m\ y^{-1}$)	0.347 ± 0.077	0.235 ± 0.034	0.754 ± 0.111	0.242 ± 0.039	0.365 ± 0.049	0.401 ± 0.106	0.390 ± 0.069	2.343 ± 0.186
Mean Linear Erosion Rate ($m\,y^{-1}$)	-0.180 ± 0.070	-0.387 ± 0.067	-0.187 ± 0.048	-0.334 ± 0.054	-0.270 ± 0.052	-0.199 ± 0.083	-0.259 ± 0.062	-1.557 ± 0.156
Mean Day of Peak Flow	152.7	162	156.3	151.5	147	155.3	154.13 ± 5.06	
Mean Peak Flow (m^3s^{-1})	11.84	11.6	12.9	12.35	11.31	10.15	11.69 ± 0.94	
Max Peak Flow (m^3s^{-1})	22.56	18.32	21.86	23.74	16.02	15.49	19.67 ± 3.53	
Mean Bankfull Duration (days)	31.3	38.1	41	36.1	29.3	25.5	33.55 ± 5.84	
Max Bankfull Duration (days)	61	48	64	63	47	31	52.33 ± 12.86	
Mean Days Above Bankfull Flow	20.3	24	22.6	23.8	18.5	12.8	20.33 ± 4.26	
Max Days Above Bankfull Flow	59	46	62	56	47	30	50.00 ± 11.71	
Mean Duration Above Baseflow (days)	215.5	218	255.1	230.9	263	278.5	243.50 ± 25.82	
Max Duration Above Baseflow (days)	362	331	364	305	364	349	345.83 ± 23.74	
Mean Days Above Baseflow	232.1	217.8	266.7	243.9	259.8	245.5	244.30 ± 17.86	
Max Days Above Baseflow	281	261	362	275	316	272	294.50 ± 37.97	
Mean Days Since Bankfull Flow	267	327.1	349.6	261.3	345.3	455.3	334.27 ± 70.58	
Max Days Since Bankfull Flow	925	904	935	579	944	901	864.67 ± 140.96	
Mean Day Baseflow Ends	280.2	288.6	304	305.3	291	321.3	298.40 ± 14.73	
Mean Day Bankfull Flow Ends	173.3	181.9	176.8	172.7	170.3	173	174.67 ± 4.11	
Mean No. Peaks Above Bankfull		1.9	2	1.8	1.4	0.5	1.52 ± 0.61	
Maximum No. Peaks Above Bankfull	3	4	5	4	3	1	3.33 ± 1.37	
Mean Total Recession Slope ($m^3\ s^{-1}\ day^{-1}$)	0.094	0.087	0.083	0.077	0.079	0.056	0.08 ± 0.01	
Max Total Recession Slope ($m^3\ s^{-1}\ day^{-1}$)	0.149	0.142	0.097	0.13	0.124	0.085	0.12 ± 0.03	
Mean Bankfull Recession Slope ($m^3\ s^{-1}\ day^{-1}$)	0.076	0.064	0.059	0.058	0.066	0.047	0.06 ± 0.01	
Max Bankfull Recession Slope ($m^3\ s^{-1}\ day^{-1}$)	0.12	0.086	0.082	0.075	0.091	0.05	0.08 ± 0.02	
Mean Total Annual Volume (km^3)	0.060	0.059	0.067	0.065	0.057	0.051	0.060 ± 0.006	
Max Total Annual Volume (km^3)	0.109	0.081	0.103	0.110	0.087	0.077	0.094 ± 0.015	
Mean Bankfull Volume (km^3)	0.027	0.034	0.037	0.033	0.027	0.024	0.031 ± 0.005	
Max Bankfull Volume (km^3)	0.074	0.047	0.072	0.073	0.050	0.031	0.058 ± 0.018	

4.3 Floodplain Vertical Accretion

Measured total depths of floodplain fine sediment above gravel and bedrock across the floodplain ranged from 0 to 141 cm with a mean value of 41 ± 25 cm (Table S2). A reach-based average migration rate of 0.24±0.05 m y^{-1} resulted in a mean migration distance of ~10.0±2.1 m along the probe transects for the entire period between 1973-2015 (Table S2). Error presented in the values above were propagated from the mean standard deviation of the estimated mean migration rates derived from the SCREAM analysis. Using our estimated vertical accretion rates at each point, we estimated an average vertical accretion rate of 3.3±0.3 cm y^{-1} among all points within the closest 10 m from the channel. The best performing multiple linear regression model explains ~60% of the variability in vertical accretion rates (r^2=0.60, p<0.001) using distance from the channel, relative elevation from the channel, valley confinement, local channel slope (all with p<0.001), and whether the survey point was on the inside of a bend (p=0.023; Table S4). A cell-by-cell multiple linear regression model of estimates of vertical accretion rates (r_{va}) across the floodplain (Figure S2) for each time period was developed based on distance from the channel (p< 0.001) and relative elevation from the channel (p<0.001). This model, readily parameterized from remotely-sensed data, explained ~54% of the variability in long-term vertical accretion rates over the 42-year time period between 1973 and 2015 (r^2=0.54, p<0.001) such that more deposition occurred closer to the channel and at lower elevations across the floodplain (Figure S2).

4.4 Eroded and Accreted Sediment Volumes

Estimated volumes of eroded and accreted sediment from the upper 2 km, intensive study reach were used to examine changes in volumes of floodplain sediment over the six time periods. Sediment input to and output from the floodplain during the six time periods ranged from 1145 ±258 to 17,324 ±2610 m^3 and 2713 ±113 to 11519 ±1851 m^3, respectively (Table 4). The difference between accreted and eroded volumes represent the net sediment change, which ranged from -6273 ±2018 (where negative values indicate net erosion) to 10,683 ±3792 m^3 of sediment (Figure 2B, Table 4).

Estimated eroded volume exceeded accreted volume in all but one (i.e., 1955-1973) of the six periods examined in this study resulting in a net loss of sediment over the total 60-year time period between 1955 and 2015 (Figure 2B). Although the resulting estimated sediment balance after 60 years was a net loss of 3919 m^3 across the floodplain during the 60-year period, this net difference falls within the error of the estimate (i.e., ±5091 m^3) and suggest closure of the sediment budget.

Table 4. Floodplain area and sediment volume eroded, accreted, and the net change between accretion and erosion along the upper 2 km, intensive study reach.

	1955 - 1973	1973 - 1983	1983 - 1990	1990 - 2001	2001 - 2011	2011 - 2015	Total
Duration (y)	18 ± 0.3	10 ± 0.3	7 ± 0.3	11 ± 0.3	10 ± 0.3	4 ± 0.3	
Area eroded (m^2)[a]	12228 ± 5060	12428 ± 2113	7341 ± 1835	16774 ± 2684	13317 ± 2530	3752 ± 1538	
Mean Depth of Eroded bank material (m)	0.54 ± 0.01	0.60 ± 0.01	0.58 ± 0.01	0.69 ± 0.01	0.61 ± 0.01	0.72 ± 0.01	
Volume Eroded (m^3)[b]	**-6640 ± 2751**	**-7476 ± 1277**	**-4272 ± 1071**	**-11519 ± 1851**	**-8080 ± 1541**	**-2713 ± 1113**	**-40700** ± 4169
Mean erosion rate (m^3/y)	-369 ± 153	-748 ± 130	-610 ± 155	-1047 ± 171	-808 ± 156	-678 ± 283	
Mean bank area erosion rate (m^2/y)[c]	-0.02 ± 0.01	-0.04 ± 0.01	-0.03 ± 0.01	-0.06 ± 0.01	-0.04 ± 0.01	-0.04 ± 0.02	
Point bar area of accretion from (m^2)[d]	28392 ± 4356	12391 ± 1735	14534 ± 2035	13612 ± 2178	14493 ± 1884	7403 ± 1851	
Mean vertical accretion within eroded areas (m)[e]	0.59 ± 0.01	0.33 ± 0.01	0.23 ± 0.01	0.36 ± 0.01	0.33 ± 0.01	0.13 ± 0.01	
Estimated accretion along point bars (m^3)[f]	16865 ± 2608	4089 ± 587	3357 ± 493	4941 ± 803	4783 ± 640	977 ± 255	
Overbank deposition (m^3)[g]	459 ± 92	302 ± 61	213 ± 44	305 ± 62	322 ± 66	168 ± 36	
Total volume accreted (m^3)[h]	**17324 ± 2610**	**4391 ± 590**	**3570 ± 495**	**5246 ± 806**	**5105 ± 643**	**1145 ± 258**	**36780** ± 2921
Mean accretion rate (m^3/y)	962.43 ± 145.87	439.11 ± 60.462	509.97 ± 73.961	476.9 ± 74.406	510.54 ± 66.126	286.16 ± 67.924	
Net volume (m^3)	**10684 ± 3792**	**-3085 ± 1407**	**-702 ± 1179**	**-6273 ± 2018**	**-2975 ± 1670**	**-1568 ± 1142**	**-3920 ± 5091**

[a] Area eroded from banks estimated by SCREAM (Rowland et al., 2016)
[b] Volume calculated directly in GIS
[c] Mean vertical area of bank eroded estimated as the mean erosion rate divided by the total channel length
[d] Area of point bar accretion estimated by SCREAM
[e] Vertical accretion estimated as the product of the duration of each time period and accretion rates derived from measured probe transect of fine floodplain sediment depths described in section 3.3
[f] Volume of accretion estimated as the product of accreted areas identified by SCREAM and mean vertical accretion rates
[g] Estimates of overbank deposition derived from the regression model described in section 3.4 in which vertical accretion rates of each DEM cell were summed and the total was multiplied by the number of years in each time period.
[h] The sum of accreted volumes from point bars and overbank deposition

4.5 Hydrologic linkages with floodplain sediment

Although each of the six time periods studied do not span equal time intervals, average flow conditions were similar for most time periods, with one drier and one wetter period (Figure 3C; Table 3). Peak discharge typically occurred within the second half of May, throughout June, and secondary peaks during high flow years sometimes occurred at the beginning of May and the beginning of July (Figure 3C; Table S3). The mean annual and peak discharges within the reach averaged 1.9 and 12.1 $m^3 s^{-1}$ respectively from 1935 to 2017. The period between 2012 and 2015 was a relatively dry interval with the least average number of days above both baseflow conditions and bankfull stage, the least mean and max annual volume of flow, the lowest maximum and mean peak flow, and the lowest mean and maximum total recession slope of all time periods (Table 3). Conversely, the period between 1991 and 2001 was a relatively wet interval with the highest mean duration above baseflow, the highest maximum peak flow, a relatively high total annual volume of discharge, and a relatively high number of peaks above bankfull flow conditions.

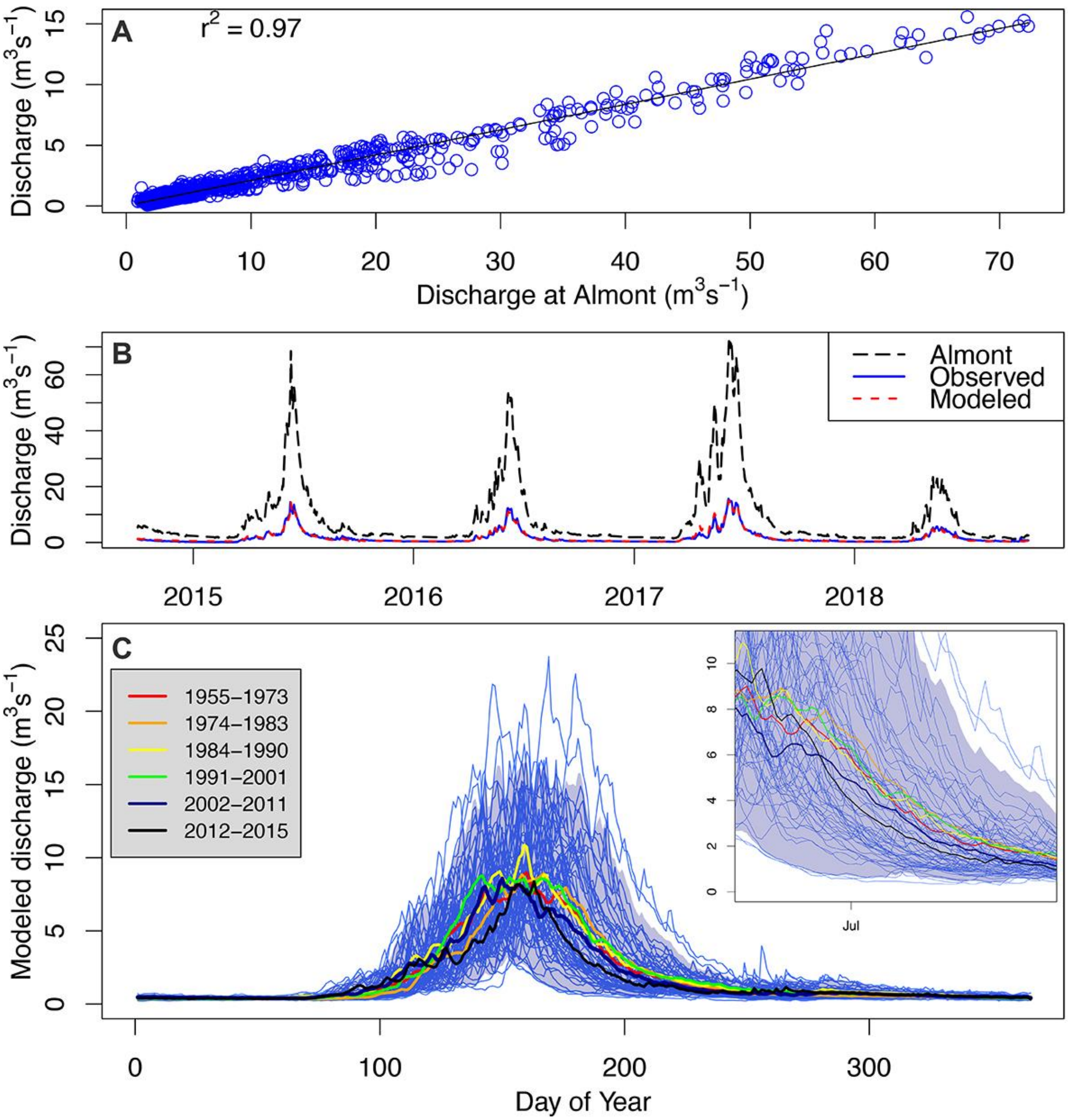

Figure 3 Modeled discharge at the East River study site and Almont stream gauge. (A) Linear regression between measured discharge at Almont and the study site (r^2=0.97), (B) discharge at the two sites for the 2015 to 2018 water years including modeled discharge at the study site based on the regression analysis (NSE=0.97). (C) Modeled annual hydrographs for the 60-year study period (1955-2015) and an inset closeup of the hydrograph recession limbs. Thin, light blue lines are annual hydrographs, the shaded blue area is the 95% confidence interval, and colored lines represent mean hydrographs for the six time periods.

Multiple stepwise linear regression indicates that floodplain sediment exchange along the nine study reaches during the six time intervals are explained primarily by the hydrologic conditions and the sinuosity of the channel at the beginning of each period (Table S5). Laterally accreted area (A_L) with the appropriate power transformation (λ = 0.2626) was most significantly influenced by a positive correlation with sinuosity (P; $p < 0.0001$), the maximum number of days above the reference baseflow condition (D_{base}; $p < 0.05$), the mean channel width (w) of the study reach (p<0.05, and the maximum bankfull recession limb slope (R_{bf}) ($r^2 = 0.55$, $p < 0.1$).

$$A_L^{0.26263} = -6.591 + 0.015D_{base} + 3.142P + 0.240w + 21.432\, R_{bf} \quad (2)$$

The area of floodplain erosion (E_A) across the nine study reaches over the 6 periods was best explained by a positive correlation with the maximum total recession limb slope from peak to baseflow conditions (R_{total}; $p<0.0001$) and sinuosity (P; $p < 0.001$) and a negative correlation with the maximum time between the first and last day flow exceeded baseflow (T_{base}) ($r^2 = 0.59$, $p < 0.05$; Table S5).

$$E_A^{0.10101} = 2.058 + 5.190\, R_{total} + 0.157\, P - 0.002\, T_{base} \quad (3)$$

Because our multiple linear regression analyses explained only about 55-60% of the variability in observed area of accretion and erosion and many variables examined require detailed analysis of imagery and lidar, we examined an additional simpler regression model using only the most significant variables that describe hydrologic conditions. Because sinuosity across the entire 11-km long study segment remains relatively constant and channel width similarly adjusts on a decadal time scale (Tables 1, 2), channel morphology maintains a quasi-steady state over the course of the study period. This means that changes in erosion and accretion may be explained by hydrology alone on a larger scale, under the primary assumptions of consistent sediment supply proportional to discharge. Such an approach is appealing because changes in hydrology are more easily measured by stream gauging, which allows predictions using future projections in climate variability.

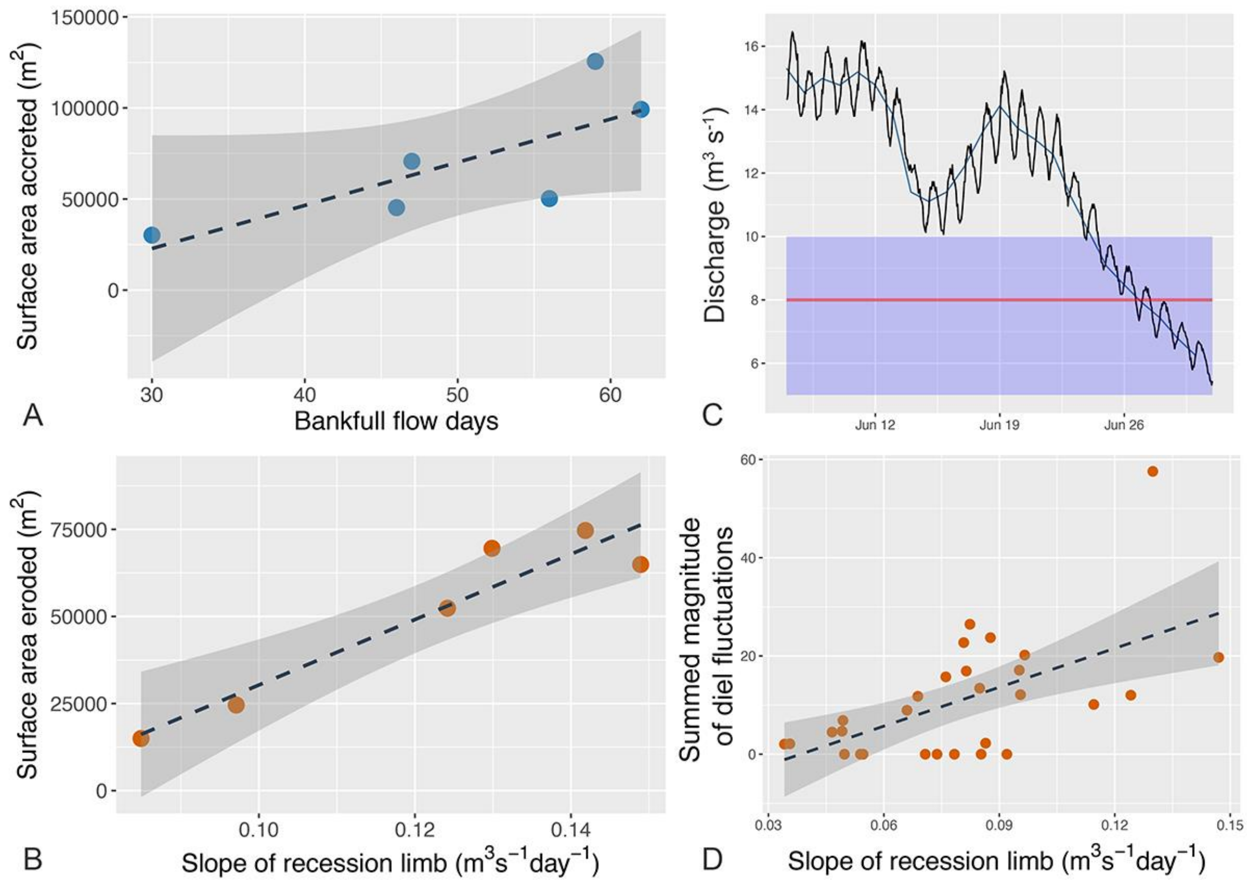

Figure 4 Linear regression of eroded and accreted areas and diel fluctuations. Each point represents each of the six time intervals for which data from all nine study reaches are combined. (A) The number of days that flow exceeded bankfull flow conditions is a significant predictor of accreted area (r^2=0.59, p = 0.074) and (B) the maximum slope within each time frame of the total recession limb from peak to baseflow is a significant predictor of eroded area (r^2=0.91, p = 0.003). (C) Fluctuations in discharge in response to snowmelt during daily warming and cooling cycles can exceed 3 m^3 s^{-1}, but do not show a strong correlation with the slope of the recession limb (r^2=0.29) (D). In A, B, and D, the dashed lines represent the linear regression model and the gray shaded area represents the 95% confidence intervals. In C the red line represents the bankfull flow stage and the blue shaded area represents the window in which diel fluctuations were examined.

Our analysis did not show a strong correlation between the maximum slope of the recession limb and number of, the summed magnitude, or the mean magnitude of diel fluctuations in discharge (Q = 8 m^3s^{-1}) within the defined bankfull window ($5 < Q_{bf} < 12$ m^3s^{-1}), but this topic requires more attention, particularly in snowmelt-dominated system that could change under a shifting climate.

Multiple linear regression to examine the role of hydrologic drivers alone on floodplain sediment dynamics across the entire 11-km long study segment – in contrast to the regression analyses that examined morphologic variables in addition to hydrologic variable across the nine study reaches – identified similar variables as the most significant predictors of erosion and accretion found in those other regression analyses. Examining hydrology alone, lateral accretion across the entire 11-km long study segment was best explained by the maximum number of days flow was above bankfull stage ($r^2 = 0.59$, $p = 0.074$; Figure 4A). The most significant hydrologic variable for explaining the area of erosion along the 11-km long study segment was the mean slope of the hydrograph recession from peak to baseflow conditions ($r^2 = 0.91$, $p = 0.003$; Figure 4B).

4. Discussion

4.1 Temporal variability of channel widening and narrowing

On the East River, we observed that progressive increases in sinuosity were truncated by channel cutoffs. This autocylic pattern was punctuated with alternating periods of channel narrowing and widening, which occur in tandem to maintain a relatively stable sinuosity on the order of decades over the 11-km long study segment (Table 1; Figure 2A). The period between 2012 and 2015 is the only exception in this alternating pattern and may have arisen from a reduction in erosion associated with the lowest maximum total recession slope in the study period. Channel reaches are more likely to experience deposition and lateral accretion following channel widening as flows spread out, flow depth decreases, and competency to transport sediment declines. Germination of riparian species during high flows stabilize point bars, resulting in channel narrowing that can force flow to outer banks and encourage subsequent bank erosion (Merritt & Cooper, 2000; Zen et al., 2017). This type of feedback appears to have occurred on the East River where narrowing induced increases in flow depth, velocity, and boundary shear stress would have driven bank undercutting of the fine sediment facilitating cantilever failure of saturated banks. Thus a window of opportunity for vegetation establishment on bars (Balke et al., 2014; Caponi et al., 2019) followed by a substantial duration of overbank flow that undercut banks would facilitate such a cyclical pattern. Propagation of cyclical patterns of narrowing and widening have commonly been observed in the field (Hooke, 2008; Cantelli et al., 2004) and modeled to match field observations after channel avulsions or bifurcations (Kleinhans et al., 2011) like the chute cutoffs that occur on the East River.

4.2 Balancing the floodplain sediment budget and accretion

Of all the sources of possible error (i.e., lateral erosion and accretion, interpolation of sediment volumes across the channel, and estimates of floodplain vertical accretion), vertical accretion represents the most uncertain component of the sediment budget. Estimates of deposition along point bars and areas adjacent to the channel are relatively robust because they are based on measured long-term average deposition rates, but overbank deposition across the entire floodplain based on our multiple linear regression contains uncertainty that cannot fully be quantified. Our approach used a bulk depth of total sediment deposited over the 42 year period between 1973 and 2015, which does not account for deposition and subsequent erosion occurring at time scales shorter than our averaging.

Our regression analysis of lateral accretion does however examine hydrologic indices that can incorporate the influences of annual events into the time period in which those events occur (e.g., maximum bankfull volume, maximum cumulative days since last bankfull flow). The duration between flow events has been referred to as the “window of opportunity” for riparian vegetation to germinate and has been shown to be highly correlated with point bar accretion (Balke et al., 2014; Zen et al., 2017; Caponi et al., 2019). Correlation were low between lateral accretion and the maximum (r=0.232) and mean (r=-0.346) cumulative days since the last bankfull flow and although the latter was higher, our results indicate a negative correlation

(Table S6). These variables were also eliminated for consideration in the optimal stepwise linear regression model because of cross correlation ($r = -0.79$) with the most significant hydrologic variable in the regression analysis, duration of overbank flow exceeding bankfull stage.

Our results linking (1) duration of overbank flows to lateral accretion and (2) distance from the channel and relative elevation with overbank deposition support published research that documents overbank deposition as a function of the duration of inundation and distance from the channel (Asselman & Middelkoop, 1995; Hupp et al., 2008; G. Day et al., 2008).

4.3 *Linkages between hydrology and observed bank erosion*

Although the study presented here does not examine annual trends, our multiple regression analysis results of nine study reaches and the simple relationship in Figure 4B suggests that the slope of the peak annual recession limb is strongly linked to the occurrence of bank erosion on the East River. While sinuosity and the maximum duration between the first and last day of flow exceeding baseflow conditions are also significant predictors in the multiple linear regression analysis ($p<0.01$), the recession limb slope has a higher significance ($p<0.0001$). Although the volume of discharge above bankfull flow has been shown to be linked to erosion (Surian, et al., 2015), this variable was eliminated from the analysis as a potential predictor because of a strong correlation with the mean number of bankfull days ($r=0.98$). Other variables eliminated from consideration as predictors for erosion because of high correlation with the maximum total recession limb include variants of: the duration of baseflow, the bankfull slope of the recession limb, and the cumulative number of days since the last bankfull flow.

The importance of the recession limb slope is emphasized by the fact that the maximum total recession slope alone explains 91% of the variability in bank erosion when considering the entire 11-km long study segment without separation into the nine study reaches. Past work by Pizzuto (1994) in a snowmelt dominated system determined that elevated discharge for approximately 7 days on the Powder River, Montana suggested a steep recession limb in 1978 may have been partially responsible for observed bank erosion on the order of 30% of the channel width. Temporal resolution of aerial imagery does not provide the frequency needed to examine past erosion on annual time scales on the East River. Hooke (1979) outlined a similar challenge when examining the connection between bank erosion and hydrologic flow conditions in temperate systems, because the study lacked the temporal resolution necessary to examine the role of the recession limb in the observed rainfall-induced storm hydrograph peaks. The role of the recession limb as a mechanism for bank erosion, however, likely varies substantially between the temperate stormy system examined by Hooke and snowmelt-dominated discharge of the East River.

Several mechanisms for river bank failures have been identified in prior research, as described briefly in the introduction, but findings presented here that link flow conditions to erosion may include a combination of mechanisms. On the East River, we observed that high flows eroded underlying fluvial gravels resulting in planar cantilever failures of the fine grained upper portion of the bank (Figure 1D, S1). Bank failures as a result of changes in river stage may be triggered by a loss of confining pressure or slip failures resulting from positive pore pressure, where slow drainage in saturated overlying banks of fine sediment cannot drain fast enough to keep pace with the decline in stage (Rinaldi & Casagli, 1999). Positive pore pressure is likely the case in stormy systems that experience flash floods with dramatic changes in discharge occurring over the course of a single day or several hours, but could likely play a partial role in bank erosion on the East River.

Shifting oblique directions in subsurface hydraulic gradient observed on the East River (Malenda et al., 2019), could change the magnitude and direction of confining pressure on the outside of river bends where erosion occurs and shifts hyporheic flow toward apposing meander bends. This change in hydraulic gradient could produce a positive pore pressure along banks with a seepage face, triggering bank erosion (Rinaldi & Casagli, 1999; Fox et al., 2007).

Although it is possible that some bank failures in the study area have been triggered by positive pore pressure, these types of failures often occur along much higher banks (>4m) composed of heterogeneous bank material, and slump scarps commonly provide evidence of occurrence (Simon et al., 2000; Langendoen & Simon, 2008; S. S. Day et al., 2013b). Slumps scarps are not observed on the East River, and cantilevers failures are the primary mechanism of bank failure.

Loss in confining pressure, provides a conceptual explanation for the link between observed cantilever failures and the slope of the recession limb in our analysis. Following undercutting during flows at or exceeding bankfull discharge, the gradual decline in flow stage occurring over the course of days to weeks and characteristic of snowmelt-dominated systems is likely to allow silt-dominated soils to drain so that undercut banks are no longer fully saturated (Figure 4). The loss of supporting pressure with declining stage can result in tension cracks of undercut banks that trigger bank failure (Rinaldi & Casagli, 1999). These cracks can be exacerbated by the weight of nearly saturated banks and repeat loss of supporting pressure from large diel fluctuations in discharge (2 to 5 m^3s^{-1}) during peak flow recessions on the East River near bankfull stage (~8 m^3s^{-1}; Figure 4C). These rapid changes in discharge (Q) equate to daily changes in flow depth (d) of approximately 20 to 30 cm at the gauging station which has an approximate bankfull width (w) of 14 m. Our analysis of diel fluctuations on an hourly time step from using USGS gage data from 1988 to 2018, however, does not show a strong correlation with the slope of the recession limb (Figure 4D), but this possible mechanism requires additional attention.

4.4 Influence of shifting hydrologic regimes on floodplain sediment fluxes

Observed increases in erosion linked to the total slope of the annual recession limb along the snowmelt-dominated East River in CO are likely to exist in other snowmelt-dominated systems that constitute a majority of rivers in the western USA (Li et al., 2017) and rivers above

40° latitude globally (Adam et al., 2009). Predicted increase in the frequency and severity of storms and floods (Bates et al., 2008) could make extreme floods in mountainous regions – like the one that occurred in the Colorado Front Range in 2013 – more common, which could greatly alter floodplain sediment dynamics and residence times (Sutfin & Wohl, 2019). Observed changes in snowpack (Stewart, 2009), upward shifts in the rainfall-snowfall transition (Kampf & Lefsky, 2016), rapid warming and earlier snowmelt (Clow, 2009), increased rain-on-snow events, are altering snow-melt dominated hydrographs (Stewart et al., 2004; Clow, 2009; Kampf & Lefsky, 2016; Praskievicz, 2016; Painter et al., 2018). The coldest snowmelt regimes are likely to experience increased spring hydrograph peaks, whereas transitional snowmelt regimes may experience lower spring peaks and more winter peak events (Nijssen et al., 2001). Rain-on-snow events in winter months could produce hydrograph peaks that exceed spring peaks in snowmelt dominated systems. Although observations and projections of floods do not indicate an increase in magnitude across rivers with all types of flow regimes, floods are occurring more often (Hirsch & Archfield, 2015; Mallakpour & Villarini, 2015), which means more variability and more frequent recession limbs in otherwise predictable and consistent snowmelt-dominated systems. These changes would by definition shift otherwise predictable snowmelt dominated systems to more flashy systems with increased variability and more rapidly rising and receding limbs, but how changes could influence sediment dynamics are uncertain.

The changes in annual average snowpack and timing of snowmelt are poised to change the variables identified in this study as important for both erosion and accretion, but the direction of these changes in unknown. If a link between diel fluctuations and recession slope exists in snowmelt-dominated systems stronger than that presented here, increased frequency of flood peaks may not result in a substantial increase in bank erosion. However, if the link between the recession slope and cantilever bank erosion occurs independently of diel fluctuations, increased frequency and flashiness of flood peaks could equate to a significant increase in bank erosion and alteration of floodplain sediment budgets. Because our results and other studies have shown a positive correlation between floodplain accretion and the duration of overbank flow (Asselman & Middelkoop, 1995; Hupp et al., 2008), flashier systems could limit overbank deposition while encouraging bank erosion.

Conclusion

Analysis of aerial imagery, aerial lidar data, and field measurements of depth of floodplain fine sediment suggest that the floodplain sediment budget along the East River study segment is balanced over the 60-year study period. Empirical relationships between 60 years of discharge data, channel morphometry of nine study reaches, and observed bank erosion and accretion suggest that channel sinuosity is a significant factor for both erosion and accretion and that channel width is a significant factor for the latter. In addition, the maximum slope of the recession limb from the peak to baseflow and bankfull stage to baseflow as well as the duration of flow above baseflow and bankfull conditions are significant hydrologic indices correlated with erosion and accretion. The role of the hydrologic variables becomes more evident when erosion and accretion are examined across the entire 11-km long study segment, rather than the nine study reaches. Sixty percent of the variability in accretion is explained by the maximum number of flow days exceeding bankfull stage and 91% of erosion is explained by the maximum slope of the annual peak recession limb within each time period. We posit that diel fluctuations during the annual recession on the order of 25% of the bankfull flow play a role in observed cantilever failures, but our analysis does not show a strong relationship between recession slope and diel fluctuations. Projected changes and increased variability in flow regimes of snowmelt-dominated systems are likely to influence the variables identified here as important for floodplain sediment dynamics in other regions.

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Year	Floodplain area (km2)	Channel Area (km2)	Channel Length (km)	Sinuosity (m/m)	Channel slope (%)
1955	2193.6	459.0	20.08	1.89	0.339%
1973	2254.0	398.7	19.29	1.82	0.353%
1983	2222.3	430.3	18.80	1.77	0.362%
1990	2295.4	357.3	18.90	1.78	0.361%
2001	2275.4	377.3	19.39	1.83	0.352%
2011	2296.2	356.5	18.81	1.77	0.362%
2015	2312.2	340.4	18.98	1.79	0.359%

Confinement (m2/m2)	Mean channel width (m)
0.17	25 ± 2
0.15	20 ± 2
0.16	23 ± 3
0.13	19 ± 3
0.14	21 ± 3
0.13	19 ± 1
0.13	17 ± 1

Reach	Valley area (m^2)	Valley Length (m)	Valley slope (%)	Floodplain area (m^2)	Channel Area (m2)
1	344236	1471	0.94	294462	49774 ± 6292
2	489119	2126	0.74	405784	83334 ± 6234
3	232658	910	0.55	199873	32785 ± 6046
4	93445	595	0.86	76134	17311 ± 1495
5	330488	1142	0.68	283494	46994 ± 5334
6	378666	924	0.56	344169	34497 ±4194
7	302210	855	0.33	271371	30839 ± 6166
8	126101	1175	0.54	89108	36992 ± 2469
9	355743	1420	0.46	299779	55965 ± 8114

Channel Length (m)	Sinuosity (m/m)	Channel slope (%)	Confinement (m^2/m^2)	Channel
2860 ± 130	1.94 ± 0.09	0.48 ± 0.02	0.14 ± 0.02	18
4735 ± 143	2.23 ± 0.07	0.33 ± 0.01	0.17 ± 0.01	18
1740 ± 99	1.91 ± 0.11	0.29 ± 0.02	0.14 ± 0.03	19
903 ± 60	1.52 ± 0.10	0.57 ± 0.04	0.19 ± 0.02	20
2419 ± 170	2.12 ± 0.15	0.32 ± 0.02	0.14 ± 0.02	20
1448 ± 248	1.57 ± 0.27	0.37 ± 0.06	0.09 ± 0.01	22
1490 ± 116	1.74 ± 0.14	0.19 ± 0.02	0.1 ± 0.02	21
1583 ± 26	1.35 ± 0.02	0.4 ± 0.01	0.29 ± 0.02	23
2001 ± 53	1.41 ± 0.04	0.33 ± 0.01	0.16 ± 0.02	23

width (m)
± 3
± 2
± 3
± 2
± 2
± 3
± 3
± 3
± 4

	1955-1973	1973-1983	1983-1990	1990-2001	2001-2011	2011-2015	Mean	Total
Duration (years)	18 ± 0.3	10 ± 0.3	7 ± 0.3	11 ± 0.3	10 ± 0.3	4 ± 0.3	10 ± 0.3	60 ± 0.8
Accretion (m^2)	125529 ± 27774	45276 ± 6339	99194 ± 13887	50226 ± 8036	70686 ± 9189	30156 ± 7539	70178 ± 12127	421067 ± 34789
Erosion (m^2)	-64915 ± 25388	-74670 ± 12694	-24569 ± 6142	-69550 ± 11128	-52358 ± 9948	-14969 ± 6137	-50172 ± 11906	-301031 ± 33224
Net Change (m^2)	60614 ± 37629	-29394 ± 14188	74625 ± 15185	-19324 ± 13726	18328 ± 13543	15187 ± 9721	20006 ± 17332	120036 ± 48106
Accretion Rate ($m^2 y^{-1}$)	6974 ± 1548	4528 ± 652	14171 ± 2095	4566 ± 744	7069 ± 949	7539 ± 1987	7474 ± 1329	44846 ± 3551
Erosion Rate ($m^2 y^{-1}$)	-3606 ± 1412	-7467 ± 1294	-3510 ± 893	-6323 ± 1030	-5236 ± 1010	-3742 ± 1566	-4981 ± 1201	-29884 ± 2999
Mean linear Accretion Rate ($m\ y^{-1}$)	0.347 ± 0.077	0.235 ± 0.034	0.754 ± 0.111	0.242 ± 0.039	0.365 ± 0.049	0.401 ± 0.106	0.390 ± 0.069	2.343 ± 0.186
Mean Linear Erosion Rate ($m\ y^{-1}$)	-0.180 ± 0.070	-0.387 ± 0.067	-0.187 ± 0.048	-0.334 ± 0.054	-0.270 ± 0.052	-0.199 ± 0.083	-0.259 ± 0.062	-1.557 ± 0.156
Mean Day of Peak Flow	152.7	162	156.3	151.5	147	155.3	154.13 ± 5.06	
Mean Peak Flow ($m^3 s^{-1}$)	11.84	11.6	12.9	12.35	11.31	10.15	11.69 ± 0.94	
Max Peak Flow ($m^3 s^{-1}$)	22.56	18.32	21.86	23.74	16.02	15.49	19.67 ± 3.53	
Mean Bankfull Duration (days)	31.3	38.1	41	36.1	29.3	25.5	33.55 ± 5.84	
Max Bankfull Duration (days)	61	48	64	63	47	31	52.33 ± 12.86	
Mean Days Above Bankfull Flow	20.3	24	22.6	23.8	18.5	12.8	20.33 ± 4.26	
Max Days Above Bankfull Flow	59	46	62	56	47	30	50.00 ± 11.71	
Mean Duration Above Baseflow (days)	215.5	218	255.1	230.9	263	278.5	243.50 ± 25.82	
Max Duration Above Baseflow (days)	362	331	364	305	364	349	345.83 ± 23.74	
Mean Days Above Baseflow	232.1	217.8	266.7	243.9	259.8	245.5	244.30 ± 17.86	
Max Days Above Baseflow	281	261	362	275	316	272	294.50 ± 37.97	
Mean Days Since Bankfull Flow	267	327.1	349.6	261.3	345.3	455.3	334.27 ± 70.58	
Max Days Since Bankfull Flow	925	904	935	579	944	901	864.67 ± 140.96	
Mean Day Baseflow Ends	280.2	288.6	304	305.3	291	321.3	298.40 ± 14.73	
Mean Day Bankfull Flow Ends	173.3	181.9	176.8	172.7	170.3	173	174.67 ± 4.11	
Mean No. Peaks Above Bankfull		1.9	2	1.8	1.4	0.5	1.52 ± 0.61	
Maximum No. Peaks Above Bankfull	3	4	5	4	3	1	3.33 ± 1.37	
Mean Total Recession Slope ($m^3 s^{-1} day^{-1}$)	0.094	0.087	0.083	0.077	0.079	0.056	0.08 ± 0.01	
Max Total Recession Slope ($m^3 s^{-1} day^{-1}$)	0.149	0.142	0.097	0.13	0.124	0.085	0.12 ± 0.03	
Mean Bankfull Recession Slope ($m^3 s^{-1} day^{-1}$)	0.076	0.064	0.059	0.058	0.066	0.047	0.06 ± 0.01	
Max Bankfull Recession Slope ($m^3 s^{-1} day^{-1}$)	0.12	0.086	0.082	0.075	0.091	0.05	0.08 ± 0.02	
Mean Total Annual Volume (km^3)	0.060	0.059	0.067	0.065	0.057	0.051	0.060 ± 0.006	
Max Total Annual Volume (km^3)	0.109	0.081	0.103	0.110	0.087	0.077	0.094 ± 0.015	
Mean Bankfull Volume (km^3)	0.027	0.034	0.037	0.033	0.027	0.024	0.031 ± 0.005	
Max Bankfull Volume (km^3)	0.074	0.047	0.072	0.073	0.050	0.031	0.058 ± 0.018	

	1955 - 1973	1973 - 1983	1983 - 1990	1990 - 2001	2001 - 2011	2011 - 2015	Totals
Duration (y)	18 ± 0.3	10 ± 0.3	7 ± 0.3	11 ± 0.3	10 ± 0.3	4 ± 0.3	
Area Eroded from SCREAM (m^2)	12228 ± 5060	12428 ± 2113	7341 ± 1835	16774 ± 2684	13317 ± 2530	3752 ± 1538	
Mean Depth of Eroded (m)	0.54 ± 0.01	0.60 ± 0.01	0.58 ± 0.01	0.69 ± 0.01	0.61 ± 0.01	0.72 ± 0.01	
Volume Eroded (m^3)	**-6640 ± 2751**	**-7476 ± 1277**	**-4272 ± 1071**	**-11519 ± 1851**	**-8080 ± 1541**	**-2713 ± 1113**	**-40700** ± 4169
Mean erosion rate (m^3/y)	-369 ± 153	-748 ± 130	-610 ± 155	-1047 ± 171	-808 ± 156	-678 ± 283	
Mean bank area erosion rate (m^2/y)[c]	#REF! ± #REF!	#REF! ± #REF!	#REF! ± #REF!	#REF! ± #REF!	#REF! ± #REF!	#REF! ± #REF!	
Point bar area of accretion from SCREAM (m^2)	28392 ± 4356	12391 ± 1735	14534 ± 2035	13612 ± 2178	14493 ± 1884	7403 ± 1851	
Mean vertical accretion within eroded areas (m)	0.59 ± 0.01	0.33 ± 0.01	0.23 ± 0.01	0.36 ± 0.01	0.33 ± 0.01	0.13 ± 0.01	
Estimated accretion along point bars (m^3)	16865 ± 2608	4089 ± 587	3357 ± 493	4941 ± 803	4783 ± 640	977 ± 255	
Overbank deposition from regression (m^3)	459 ± 92	302 ± 61	213 ± 44	305 ± 62	322 ± 66	168 ± 36	
Total volume accreted (m^3)	**17324 ± 2610**	**4391 ± 590**	**3570 ± 495**	**5246 ± 806**	**5105 ± 643**	**1145 ± 258**	**36780** ± 2921
Mean accretion rate (m^3/y)	962.43 ± 145.87	439.11 ± 60.462	509.97 ± 73.961	476.9 ± 74.406	510.54 ± 66.126	286.16 ± 67.924	
Net volume (m^3)	**10684 ± 3792**	**-3085 ± 1407**	**-702 ± 1179**	**-6273 ± 2018**	**-2975 ± 1670**	**-1568 ± 1142**	**-3920 ± 5091**

Figure 1.

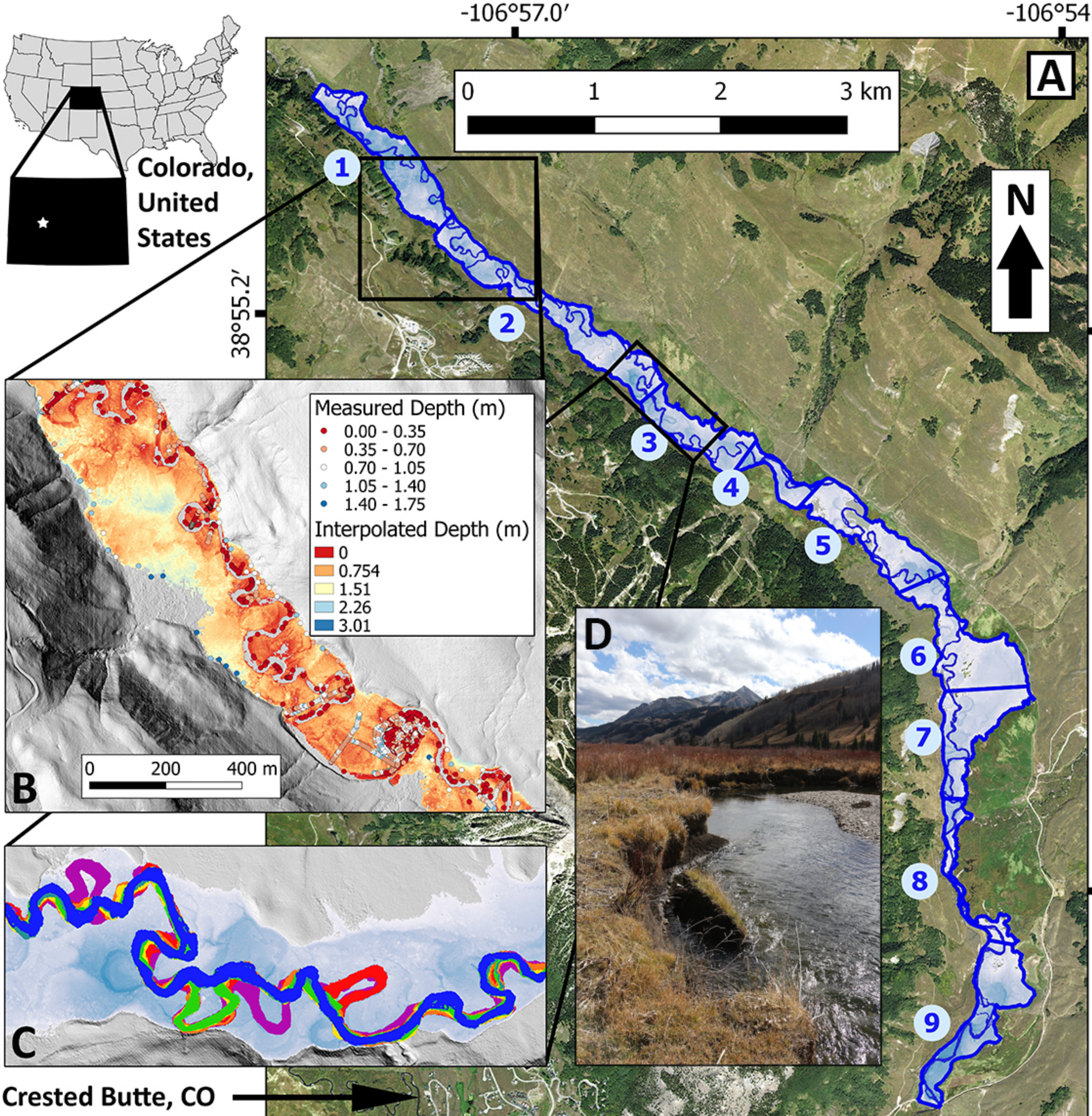
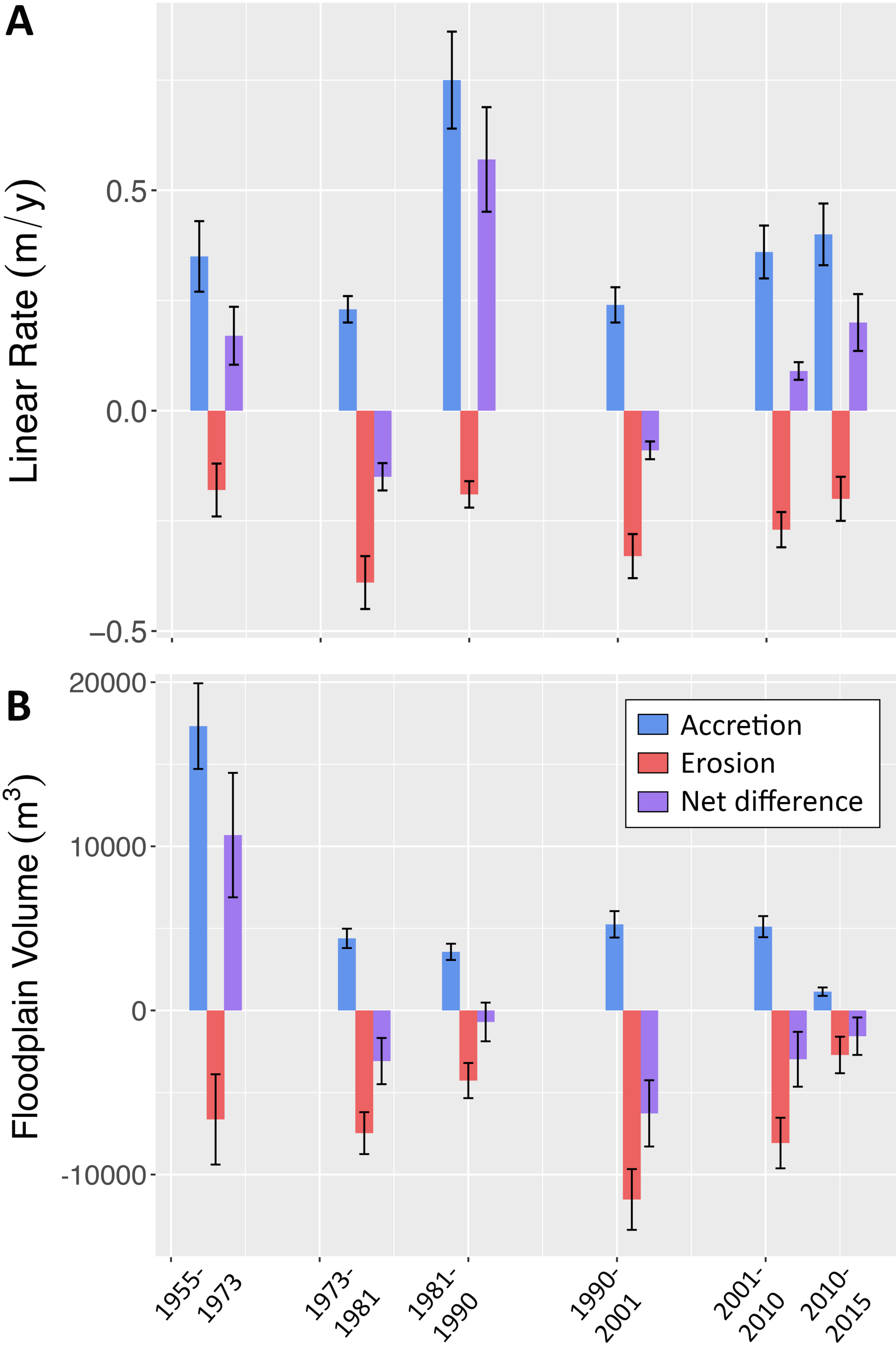
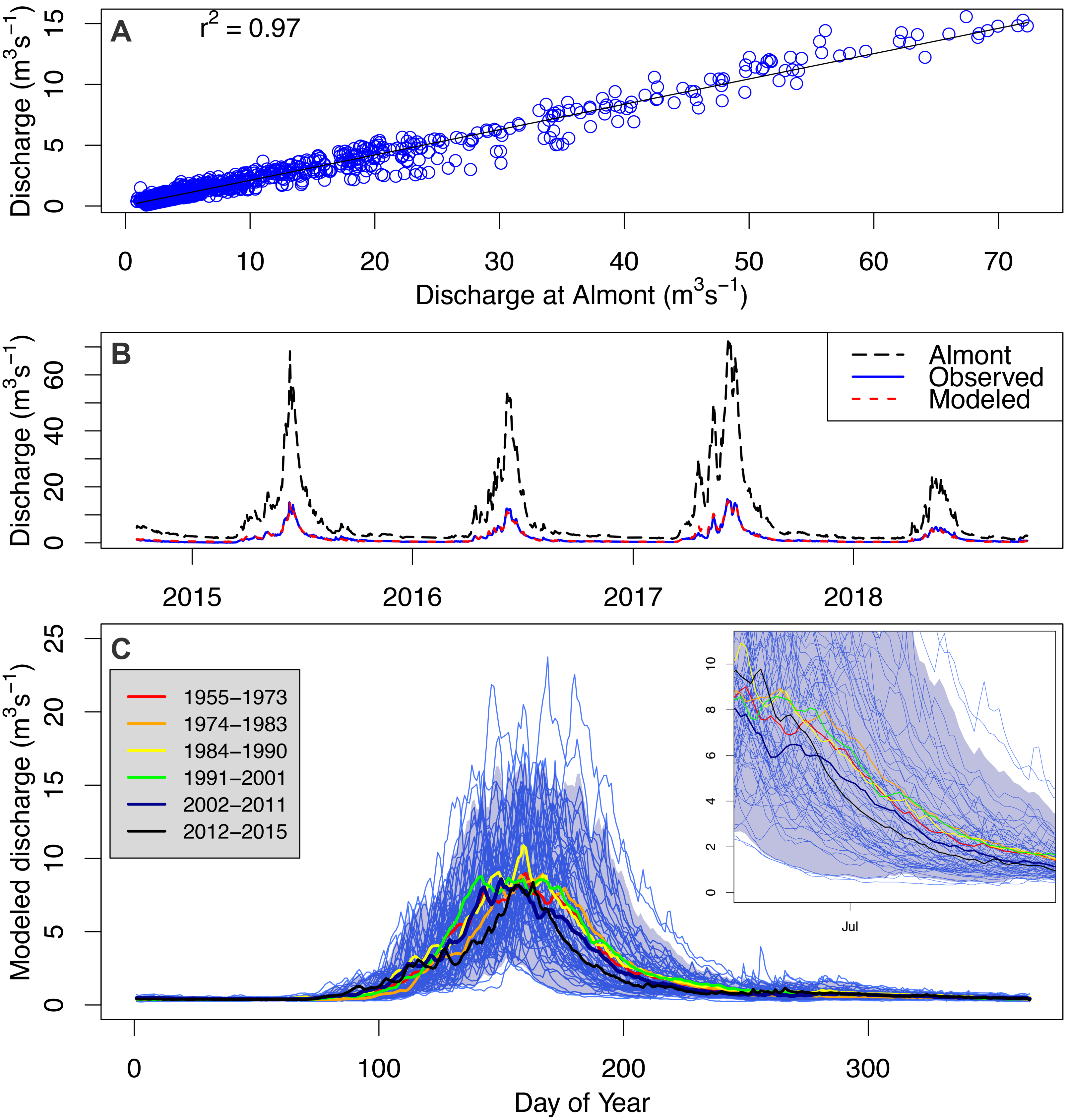

-106°57.0′
-106°54.0′
38°55.2′
38°52.8′
A
0
1
2
3 km
N
Colorado,
United
States
1
2
3
4
5
6
7
8
9
Measured Depth (m)
0.00 - 0.35
0.35 - 0.70
0.70 - 1.05
1.05 - 1.40
1.40 - 1.75
Interpolated Depth (m)
0
0.754
1.51
2.26
3.01
0
200
400 m
B
C
D
Crested Butte, CO

Figure 2.



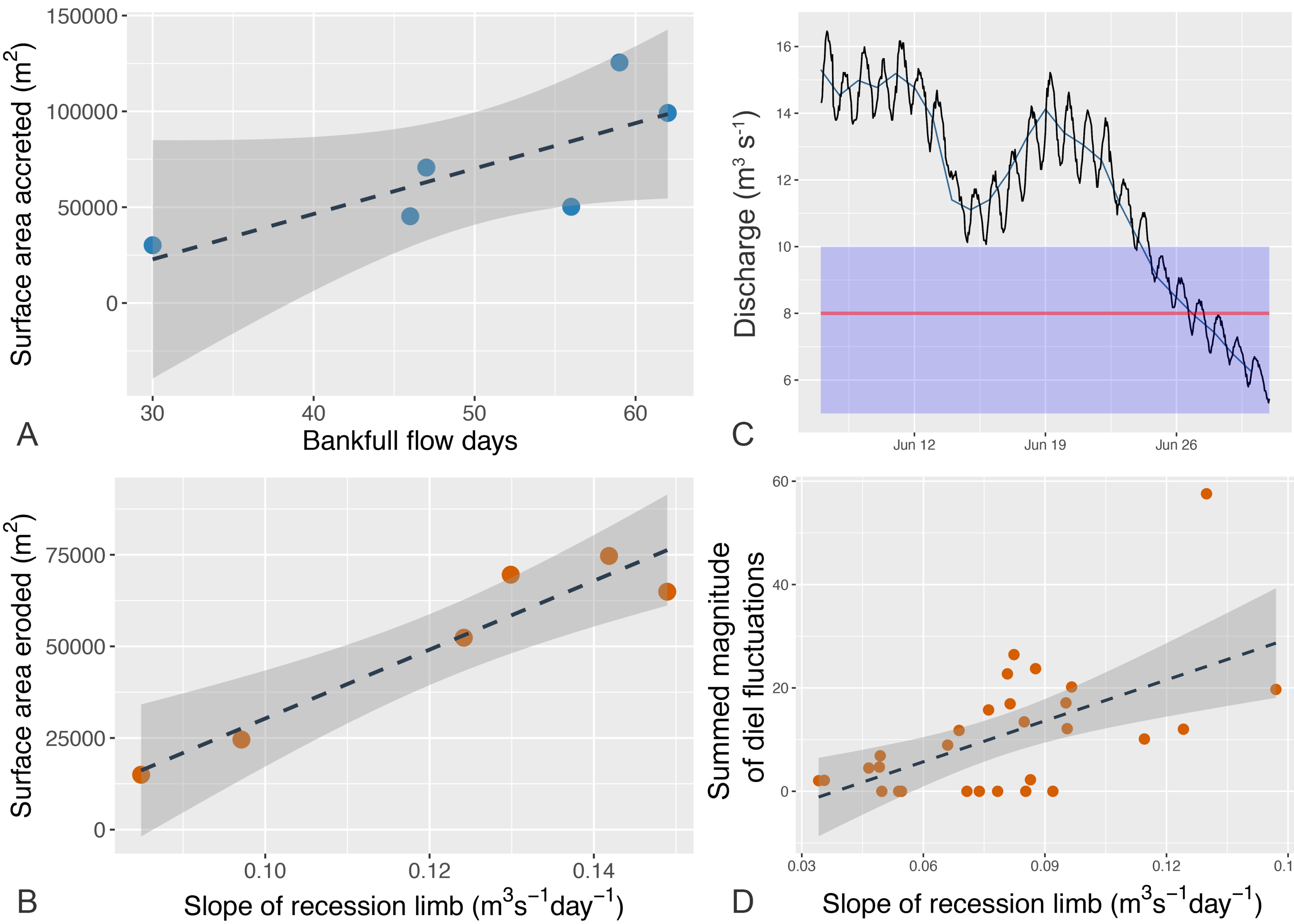
A
Linear Rate (m/y)
0.5
0.0
−0.5
B
Floodplain Volume (m3)
20000
10000
0
-10000
Accretion
Erosion
Net difference
1955-1973
1973-1981
1981-1990
1990-2001
2001-2010
2010-2015

Figure 3.



A
$r^2 = 0.97$
Discharge (m^3s^{-1})
Discharge at Almont (m^3s^{-1})
0
5
10
15
20
30
40
50
60
70
B
Almont
Observed
Modeled
Discharge (m^3s^{-1})
2015
2016
2017
2018
C
1955–1973
1974–1983
1984–1990
1991–2001
2002–2011
2012–2015
Modeled discharge (m^3s^{-1})
Jul
Day of Year
0
100
200
300

Figure 4.


Surface area accreted (m^2)
150000
100000
50000
0
30
40
50
60
Bankfull flow days
A
Discharge (m^3 s^{-1})
16
14
12
10
8
6
Jun 12
Jun 19
Jun 26
C
Surface area eroded (m^2)
75000
50000
25000
0
0.10
0.12
0.14
Slope of recession limb (m^{3}s^{-1}day^{-1})
B
Summed magnitude of diel fluctuations
60
40
20
0
0.03
0.06
0.09
0.12
0.15
Slope of recession limb (m^{3}s^{-1}day^{-1})
D

```
# This code will examine to hydrograph dataset, select matching days
# and times and conduct a regression that can be used to fill in missing data
# Author: Nicholas A. Sutfin
# Date: Oct. 18th 2017, last modified May 8th, 2020

library("plyr")
#library("smwrBase", lib.loc="~/R/win-library/3.2")
library("lattice") #, lib.loc="C:/Program Files/R/R-3.3.0/library")
library("lubridate")
library("hydroGOF")

# Set user space
loadpath = '/Users/NicholasSutfin/Documents/EastRiver/ER_Rcode/'
savepath = '/Users/NicholasSutfin/Documents/EastRiver/ER_Rcode/Baseflow_1.91_BestFit/' #
Calculating slope as line between 1st and last points (2p)
setwd(loadpath)

All_DailyQ_1935_2020 = read.csv("All_DailyQ_1935_2020.csv", stringsAsFactors = F)
#"All_DailyQ_1910_2020.csv", stringsAsFactors = F)

# Load ALmont data for 2015-2017 as csv file, convert to SI units, code the date as a date, and
define the year
Alm_Q <- read.csv("ER_AlmQ_2015-2019.csv", header=TRUE)
Alm_Q$Q_cfs = as.numeric(as.character(Alm_Q$Q_cfs))
Alm_Q$Alm_Q_cms = Alm_Q$Q_cfs*0.0283168
Alm_DailyQ = as.data.frame(Alm_Q)
Alm_DailyQ = ddply(Alm_DailyQ, ~date, summarise, Alm_Q_cms = mean(Alm_Q_cms))
Alm_Qdaily <- Alm_DailyQ[order(as.Date(Alm_DailyQ$date, format="%m/%d/%y")),]
Alm_Qdaily$Date = as.Date(Alm_Qdaily$date, "%m/%d/%y")
Alm_Qdaily$year = year(Alm_Qdaily$Date)
Alm_Qdaily$month = month(Alm_Qdaily$Date)
Alm_Qdaily$Calday = day(Alm_Qdaily$Date)
Alm_Qdaily$day = yday(Alm_Qdaily$Date)

# Load Pump house data for 2015-2017 as csv file, convert to SI units, code the date as a date,
and define the year
#PH_Qdaily <- read.csv("ER_PH_2015-17Q.csv", header=TRUE )
PH_Data <- read.csv("ER_PHQ_2014-2018.csv", header=TRUE)
PH_DailyQ = ddply(PH_Data, ~date, summarise, PHQ_cms = mean(PHQ_cms))
PH_Qdaily <- PH_DailyQ[order(as.Date(PH_DailyQ$date, format="%m/%d/%y")),]
PH_Qdaily$Date = as.Date(PH_Qdaily$date, "%m/%d/%y")
PH_Qdaily$year = year(PH_Qdaily$Date)
PH_Qdaily$month = month(PH_Qdaily$Date)
PH_Qdaily$Calday = day(PH_Qdaily$Date)
```

```
PH_Qdaily$day = yday(PH_Qdaily$Date)
names(PH_Qdaily)[2]<-paste("PH_Q_cms")

#________________________________________________________________________________
____
# Find matching dates and create new dataset
DailyQ_diff <- setdiff(PH_Qdaily$Date, Alm_Qdaily$Date)
DailyQ_int <- intersect(PH_Qdaily$Date, Alm_Qdaily$Date)

# Find PH Q data for dates overlapping the with Almont gage
PH_DailyQ_match <- PH_Qdaily[PH_Qdaily$Date %in% DailyQ_int, ]
# Find Almont gauge data that overlaps with pump house study site data
Alm_DailyQ_match <- Alm_Qdaily[Alm_Qdaily$Date %in% DailyQ_int, ]
# Merge the two overlapping datasets side my side by matching dates
All_DailyQ_15_18 <- cbind(Alm_DailyQ_match, PH_DailyQ_match)

rows = length(All_DailyQ_15_18$PH_Q_cms) #[All_DailyQ_15_18$day > 105 &
All_DailyQ_15_18$day < 319])
Qmat <- matrix(0, rows, 3)
Q = as.data.frame(Qmat)
names(Q)[1]=paste("PH")
names(Q)[2]=paste("AL")
names(Q)[3]=paste("day")

# April 15th = 105 Nov 15th = 319, so 104-320 is good
Q$PHDate = All_DailyQ_15_18$Date[which(is.na(All_DailyQ_15_18$PH_Q_cms) == FALSE)]
#[All_DailyQ_15_18$day > 105 & All_DailyQ_15_18$day < 319]
Q$PH = All_DailyQ_15_18$PH_Q_cms[which(is.na(All_DailyQ_15_18$PH_Q_cms) == FALSE)]
#[All_DailyQ_15_18$day > 105 & All_DailyQ_15_18$day < 319]
Q$ALDate = All_DailyQ_15_18$Date[which(is.na(All_DailyQ_15_18$PH_Q_cms) == FALSE)]
#[All_DailyQ_15_18$day > 105 & All_DailyQ_15_18$day < 319]
Q$AL = All_DailyQ_15_18$Alm_Q_cms[which(is.na(All_DailyQ_15_18$Alm_Q_cms) == FALSE)]
#[All_DailyQ_15_18$day > 105 & All_DailyQ_15_18$day < 319]
Q$day = All_DailyQ_15_18$day[which(is.na(All_DailyQ_15_18$Alm_Q_cms) == FALSE)]
#[All_DailyQ_15_18$day > 105 & All_DailyQ_15_18$day < 319]

Qreg <- lm(Q$PH ~ Q$AL, data = Q)
summary(Qreg)
Qreg # adjusted R squared = 0.97

# For all days: PHQ = -0.081804 + 0.211284(Alm)
# Excluding frozen days, regression output: PHQ = 0.010948 + 0.211611(Alm)

par(mfrow=c(1,1), mar=c(4,5,2,2), cex = 1.5, lwd = 1)
```

```
plot(All_DailyQ_15_18$Alm_Q_cms, All_DailyQ_15_18$PH_Q_cms, col = "blue",
    xlab = expression(paste("Discharge at Almont (m"^"3", "s"^"-1",")")),
    ylab = expression(paste("Discharge (m"^"3", "s"^"-1",")")))
lines(All_DailyQ_15_18$Alm_Q_cms, Qreg$coefficients[1] +
Qreg$coefficients[2]*All_DailyQ_15_18$Alm_Q_cms,
     col = "black")
par(cex = 1)
#points(Q$AL, Q$PH, pch = 19, col = "red")
text(10, 15, expression("r"^{2} ~"= 0.97"), cex = 1.5)

# Load Almont discharge data from 1910 to 2020, cut data to timeframe of interest (1955-2015)
# and convert to cms
#_____________________________________________________________________________
____
Alm_Qdaily_1910_2020 <- read.csv("Alm_Q_cfs_1910_2020.csv", header=TRUE)
Alm_Qdaily_1910_2020$Alm_Q_cms = Alm_Qdaily_1910_2020$Alm_Q_cfs*0.0283168
Alm_Qdaily_1910_2020$Date = as.Date(Alm_Qdaily_1910_2020$Date, "%m/%d/%Y")

All_DailyQ_1910_2020 = Alm_Qdaily_1910_2020
All_DailyQ_1910_2020$year = format(All_DailyQ_1910_2020$Date, "%Y")
All_DailyQ_1910_2020$month = format(All_DailyQ_1910_2020$Date, "%m")
All_DailyQ_1910_2020$day = format(All_DailyQ_1910_2020$Date, "%d")
All_DailyQ_1910_2020$yday = yday(All_DailyQ_1910_2020$Date)
All_DailyQ_1910_2020$Mod_PH_Q_cms = Qreg$coefficients[1] +
Qreg$coefficients[2]*All_DailyQ_1910_2020$Alm_Q_cms

# Use regression to extend daily Q for PH based on Almont flow
#_____________________________________________________________________________
____
# regression output: PHQ = x + y(Alm)
par(mfrow=c(1,1), mar=c(4,5,3,2), cex = 1.5)
All_DailyQ_2014_2020 = All_DailyQ_1910_2020[37987:length(Alm_Qdaily_1910_2020$Date), ]

#_____________________________________________________________________________
____
# plot observed vs. modeled data for East River and calculate Nash-Sutcille and RMSE
par(mfrow=c(1,1), mar=c(4,4,2,2), cex = 1.1)

Date = All_DailyQ_2014_2020$Date
Modeled_PHQ = subset(All_DailyQ_2014_2020, Date > "2014-9-30")
#min(WaterYear15):max(WaterYear15)))

# Select only uniqe values
Observed_PHQ = All_DailyQ_15_18[,c(3,9)]
```

```
PH_Q_int <- intersect(Observed_PHQ$Date[order(Observed_PHQ$Date)],
Modeled_PHQ$Date[order(Modeled_PHQ$Date)])
Modeled_Q_match <- Modeled_PHQ[Modeled_PHQ$Date %in% PH_Q_int, ]
Observed_Q_match <- Observed_PHQ[Observed_PHQ$Date %in% PH_Q_int, ]
PHQ_15_18 = cbind(Modeled_Q_match, Observed_Q_match)

Qreg2 <- lm(PHQ_15_18$PH_Q_cms ~ PHQ_15_18$Alm_Q_cms, data = All_DailyQ_15_18)
summary(Qreg2)
Qreg2

par(mfrow=c(1,1), mar=c(4,5,2,2), cex = 1.5, lwd = 1)
# Plot Almont flow data
plot(All_DailyQ_15_18$Date, All_DailyQ_15_18$Alm_Q_cms, lwd = 2, type = "l",
   col = "black", xlab = "Year", ylab = expression(paste("Discharge (m"^"3", "s"^"-1",")")), lty =
5, cex = 1.5)
# Plot observed ER study site flow data
lines(PHQ_15_18$Date[order(PHQ_15_18$Date)],
PHQ_15_18$PH_Q_cms[order(PHQ_15_18$Date)], lty = 1, col = "blue", lwd = 2, type = "l",
   xlab = expression(paste("Discharge (m"^"3", "s"^"-1",")")), ylab = "Time (years)")
#polygon(PHQ_15_17$date, PHQ_15_17[,5], col = "blue")

# Plot modeled ER study site flow data
lines(PHQ_15_18$Date[order(PHQ_15_18$Date)],
PHQ_15_18$Mod_PH_Q_cms[order(PHQ_15_18$Date)], col = 'red', lwd = 2, lty = 2)
legend("topright", col = c("black", "blue", "red"), lty = c(5,1,2),
     lwd = 2, legend = c('Almont', 'Observed', 'Modeled'))

NSE(PHQ_15_18[,10],PHQ_15_18[,8])
text(10, 15, expression("NSE = 0.97"), cex = 1.5)
# Nash-Sutcliffe coeeficient = 0.97

#____________________________________________________________________________
_____
# Format data for hydrograph analysis
write.csv(All_DailyQ_2014_2020,"All_DailyQ_2014_2020.csv")
write.csv(All_DailyQ_1910_2020,"All_DailyQ_1910_2020.csv")

ER_Q_35_20 <- All_DailyQ_1910_2020[All_DailyQ_1910_2020$year > 1934, ]
write.csv(ER_Q_35_20, "All_DailyQ_1935_2020.csv")

####################################
# Create plots of Almont and East RIver
```

```
#_____________________________________________________________________________________
____
par(mfrow=c(1,1), mar=c(4,5,1,1), cex = 1)
All_Q_1910_2020 = All_DailyQ_1910_2020
ER_Q_55_20 <- All_Q_1910_2020[All_Q_1910_2020$year > 1954, ]

#_____________________________________________________________________________________
____
# Create a stacked plot of hydrographs for the period of record
#_____________________________________________________________________________________
____

par(mfrow=c(1,1), mar=c(4,5,2,2), cex = 1.5)

# Create an initial plot to add hydrographs from all years
plot(ER_Q_55_20$yday[ER_Q_55_20$year == 1955],
ER_Q_55_20$Mod_PH_Q_cms[ER_Q_55_20$year == 1955], type = "l",
   ylim = c(0,25), xlab = "Day of Year",
   ylab = expression(paste("Modeled discharge (m"^"3", "s"^"-1",")")), lwd = 1,
   main = "East River 1955-2015")

# Create a smaller zoomed in plot to add hydrographs from all years
#plot(ER_Q_55_20$day[ER_Q_55_20$year == 1955], ER_Q_55_20[ER_Q_55_20$year == 1955,
3], type = "l",
 #    ylim = c(0,11), xlim = c(160,220), xaxt = "n", xlab = "Day of Year", ylab = "Discharge (cms)",
lwd = 1, main = "East River 1955-2017")

# Create a list of unique years for the period of interest
years = unique(ER_Q_55_20$year)

# A for loop to plot hydrographs for all years on top of one another
for (i in 1:65) {
  years2plot = years[i]
  print(years2plot)
  dat.yr = subset(ER_Q_55_20, year == years2plot)
  print(dat.yr)
  lines(dat.yr$yday, dat.yr$Mod_PH_Q_cms, col = "royalblue1", lwd = 1)
}

# Calculate the mean and 95% confidence level for all hydrographs in the period of interest
AllFlow = ddply(ER_Q_55_20, ~yday, summarise,
            MeanFlow = mean(Mod_PH_Q_cms),
            LCI = quantile(Mod_PH_Q_cms, 0.025, na.rm = TRUE),
            UCI = quantile(Mod_PH_Q_cms, 0.975, na.rm = TRUE))
```

```
# Plot a transparent band representing the 95% confidence level
polygon(c(AllFlow$yday,rev(AllFlow$yday)),c(AllFlow$LCI,rev(AllFlow$UCI)),border=NA,
      col = rgb(red = 0.0, green = 0.0, blue = 0.5, alpha = 0.25))


#-------------------------------------------
# Plot mean hydrographs for 6 time intervals

Q_55_73 = ER_Q_55_20[ER_Q_55_20$year < 1974, ]
Q_74_83 = ER_Q_55_20[ER_Q_55_20$year > 1973 & ER_Q_55_20$year < 1984, ]
Q_84_90 = ER_Q_55_20[ER_Q_55_20$year > 1983 & ER_Q_55_20$year < 1991, ]
Q_91_01 = ER_Q_55_20[ER_Q_55_20$year > 1990  & ER_Q_55_20$year < 2002, ]
Q_02_11 = ER_Q_55_20[ER_Q_55_20$year > 2001  & ER_Q_55_20$year < 2012, ]
Q_12_17 = ER_Q_55_20[ER_Q_55_20$year > 2011, ]
Q_12_15 = ER_Q_55_20[ER_Q_55_20$year > 2011  & ER_Q_55_20$year < 2016, ]


par(mfrow=c(1,1), mar=c(4,4,2,2), cex = 1.5)

# Calculate the mean and 95% confidence level for all hydrographs in the period of interest
Flow73 = ddply(Q_55_73, ~yday, summarise,
           MeanFlow = mean(Mod_PH_Q_cms),
           LCI = quantile(Mod_PH_Q_cms, 0.025, na.rm = TRUE),
           UCI = quantile(Mod_PH_Q_cms, 0.975, na.rm = TRUE))
lines(Flow73$yday, type = "line", #ylim = c(0, 11),
     Flow73$MeanFlow, col = "red", lwd = 2.5,
    xlab = "Day of the year", ylab = "Discharge (cms)") # Plot the mean hydrograph value

# Calculate the mean and 95% confidence level for all hydrographs in the period of interest
Flow83 = ddply(Q_74_83, ~yday, summarise,
           MeanFlow = mean(Mod_PH_Q_cms),
           LCI = quantile(Mod_PH_Q_cms, 0.025, na.rm = TRUE),
           UCI = quantile(Mod_PH_Q_cms, 0.975, na.rm = TRUE))
lines(Flow83$yday,
     Flow83$MeanFlow, col = "orange", lwd = 2.5) # Plot the mean hydrograph value

# Calculate the mean and 95% confidence level for all hydrographs in the period of interest
Flow90 = ddply(Q_84_90, ~yday, summarise,
           MeanFlow = mean(Mod_PH_Q_cms),
           LCI = quantile(Mod_PH_Q_cms, 0.025, na.rm = TRUE),
           UCI = quantile(Mod_PH_Q_cms, 0.975, na.rm = TRUE))
lines(Flow90$yday,
     Flow90$MeanFlow, col = "yellow", lwd = 2.5) # Plot the mean hydrograph value
```

```
# Calculate the mean and 95% confidence level for all hydrographs in the period of interest
Flow01 = ddply(Q_91_01, ~yday, summarise,
            MeanFlow = mean(Mod_PH_Q_cms),
            LCI = quantile(Mod_PH_Q_cms, 0.025, na.rm = TRUE),
            UCI = quantile(Mod_PH_Q_cms, 0.975, na.rm = TRUE))
lines(Flow01$yday,
     Flow01$MeanFlow, col = "green", lwd = 2.5) # Plot the mean hydrograph value

# Calculate the mean and 95% confidence level for all hydrographs in the period of interest
Flow11 = ddply(Q_02_11, ~yday, summarise,
            MeanFlow = mean(Mod_PH_Q_cms),
            LCI = quantile(Mod_PH_Q_cms, 0.025, na.rm = TRUE),
            UCI = quantile(Mod_PH_Q_cms, 0.975, na.rm = TRUE))
lines(Flow11$yday,
     Flow11$MeanFlow, col = "darkblue", lwd = 3.5) # Plot the mean hydrograph value

# Calculate the mean and 95% confidence level for all hydrographs in the period of interest
Flow17 = ddply(Q_12_15, ~yday, summarise,
            MeanFlow = mean(Mod_PH_Q_cms),
            LCI = quantile(Mod_PH_Q_cms, 0.025, na.rm = TRUE),
            UCI = quantile(Mod_PH_Q_cms, 0.975, na.rm = TRUE))
lines(Flow17$yday,
     Flow17$MeanFlow, col = "black", lwd = 2.5) # Plot the mean hydrograph value

par(mfrow=c(1,1), mar=c(4,4,2,2), cex = 1.2)
legend(280, 25, legend = c("1955-1973", "1974-1983", "1984-1990", "1991-2001", "2002-2011",
"2012-2015"),
      col = c("red", "orange", "yellow", "green", "darkblue", "black"),
      lty = 1.2, lwd = 2.5, bg = "gray85")

#**********************************************************

###Stream Flow Frequency Analysis and Recession Limb Quantification

###################################
# From time lapse photos and the stage data, bankfull stage appears to occur at about 4 cms
###################################

#setwd(loadpath)
#All_DailyQ_1935_2020 = read.csv("All_DailyQ_1935_2020.csv", stringsAsFactors = F)
#"All_DailyQ_1910_2020.csv", stringsAsFactors = F)
data = All_DailyQ_1935_2020 #"All_DailyQ_1910_2020.csv", stringsAsFactors = F)
dat.er = data[ ,c(2,3,5:9)]
```

```
dat.er$flow.er = dat.er$Mod_PH_Q_cms

# estimate lowflow conditions and a reference basflow by which to measure the recession limb
Lowflow = mean(na.omit(dat.er$flow.er[dat.er$month %in% list("10","11","12","1","2","3")]))
Baseflow =  1.91 #Lowflow #mean(na.omit(dat.er$flow.er[dat.er$month %in% list("9")]))
BFQ = 8 # define a threshold approximation for bankfull discharge
# Estimated bankkfull at 8 cms

# Initialize storage variables
years = unique(dat.er$year) # Unique years for indexing (using water years (10/01-9/30))
years = years[years > 1934]

# Aggregate Yearly (or monthly) data by mean, median, max, and min (or anything else)
x = subset(dat.er, year %in% c(1935:2019))
statistics = as.data.frame(as.list(aggregate(flow.er ~ year ,data = x, FUN=function(x) c(mean
=mean(x), median=median(x), max = max(x),min = min(x)))))

maxflow = as.data.frame(matrix(ncol=10,nrow =85))#length(years)))
# define the list of column names for the dataframe
names(maxflow) = c("year","peakdate","flow.er","BFflow", "BF_EndDay", "enddate",
"TotalSlope","BFslope","BF_StartDay","PeakSlope")

for (k in 2:85){
  # Skip years where insufficient data was collected using a # of days in year as threshold. bad
  if (length(dat.er$Date[dat.er$year == years[k]]) < 250) {
  }
  else {
    # find peak flows greater than 500cfs and corresponding year and Date
    dat.sub = subset(dat.er, year == years[k]) # Subset larger data set
    dat.sub$Date = as.Date(dat.sub$Date, format="%Y-%m-%d")
    medianflow = mean(dat.sub$flow.er[dat.sub$month %in% list("10","11","12")])
 #median(na.omit(dat.sub$flow)) # find median flow (used as a threshold, need better method)
    maxflow[k,3] = max(na.omit(dat.sub$flow.er)) # find and store peak flows
    maxflow[k,1] = years[k] # store year
    index = tail(which(dat.sub$flow.er == maxflow[k,3]), n=1) # find index of peak flow to
detrmine the exact Date
    maxflow[k,2] = as.character(dat.sub$Date[index]) # Date of peak flow
    #as.Date(index, origin = dat.sub$Date[1]) #

    # Bankfull flow
    if (max(dat.sub$flow.er >= 8)) {
      indX1 = min(which(dat.sub$flow.er >= 8)) # index the date flow rises above BF
      indX = max(which(dat.sub$flow.er >= 8)) # index the date flow drops below BF
      BF_start = as.character(dat.sub$Date[indX1]) # Assign first date flow exceeds BF
```

```
    maxflow[k,9] = BF_start # Assign first date flow exceeds BF
    BF_end = as.character(dat.sub$Date[indX]) # Assign last date flow drops below BF
    maxflow[k,5] = BF_end # Assign last date flow drops below BF
    maxflow[k,4] = dat.sub$flow.er[indX]
  }
  else {
    maxflow[k,5] = NA
    maxflow[k,4] = NA
    maxflow[k,9] = NA
    indX = NA
    BF_start = NA
    BF_end = NA
    print(years[k])
    }

  ## Extracting Recession limb
  # This section finds the Dates corresponding to the peakflow (already found above) and a
later
  # Date corresponding to "normal" flow conditions. I am currently using the median but it's a
bad
  # metric.
  # Starting at the index of the peak flow Date, step forward one day (increasing the index by 1)
and
  # check if the flow that day is a certain percentage from the median value.
  PeakDate = as.character(dat.sub$Date[index]) # used for extracting recession limb
  maxdepth = maxflow[k,3] # used for extracting recession limb
  repeat{
    index = index+1
    maxdepth = dat.sub$flow.er[index] # flow one day later
    if (is.na(maxdepth)){ # check if no flow was recorded
    } else if (Baseflow > (maxdepth)){ # Check if flow is within X% of median value
      break # was preiously ((medianflow) + Qmin) > maxdepth))
      # The "index" term now identifies the obs where Q reaches a baseflow condition ~0.8cms
    } else if (index == length(dat.sub$flow.er)) {
      print(paste(dat.sub$year[1])) # identify the year
      break
      # This forces the loop to break if Q never falls below baseflow
    }
  }
 #*************************************
  # Indexing for bankfull slope calculation
  BFDate = maxflow[k,5]

  if (is.na(maxflow[k,5]) == FALSE) {
```

```
      repeat{
     indX = indX+1 #increment one more day after last BF flow
     BFQ = dat.sub$flow.er[indX] # flow one day later
     if (is.na(BFQ)){ # check if no flow was recorded and do nothing
     } else if (Baseflow > (BFQ)){ # Check if flow is within threshold of median value was
previously ((medianflow) + Qmin > (BFQ))
      break # Exist loop if Q drops below baseflow and saved that Q value as BFQ
     } else if (indX == length(dat.sub$flow.er)) {
      print(paste(dat.sub$year[1]))
      break # Exit loop if flow does not drop below baseflow
     }
    }
    }

    BaseDate = as.character(dat.sub$Date[index])
    maxflow[k,6] = as.character(dat.sub$Date[index])
    #FirstDate = dat.sub$Date[1] #Set the first date of the year

    # Convert Dates to yday for duration calculations
    BaseDay=yday(BaseDate)
    PeakDay=yday(PeakDate)
    BF_endDay=yday(BF_end)
    BF_startDay=yday(BF_start)
    Last_index=length(dat.sub$Date)
    LastDay = yday(dat.sub$Date[Last_index])
    BaseFlow_Date = as.Date(BaseDay, origin = dat.sub$Date[1])

    ##########################################################################
    # Calculate and plot slopes of recession limb at various stages
    #________________________________________________________________________

    # Calculate recession slope based on best fit regression line between all points
    TotSlopeQ = dat.sub$Mod_PH_Q_cms[dat.sub$yday %in% c(PeakDay:BaseDay)]
    TotSlopeDate = dat.sub$Date[dat.sub$yday %in% c(PeakDay:BaseDay)]
    TotSlopeReg = lm(TotSlopeQ ~ TotSlopeDate)
    summary(TotSlopeReg)

    maxflow[k,7] = -1*TotSlopeReg$coefficients[2] #((maxflow[k,3])-Baseflow)/(BaseDay-
PeakDay) # Slope of line from start to end of recession limb
    plot(dat.sub$Date, dat.sub$Mod_PH_Q_cms, type = "line", main = paste(years[k]),
       ylab = "Discharge (cms)", xlab = NA)
    points(TotSlopeDate, TotSlopeQ, pch = 19, col = "violet")
    lines(TotSlopeDate, predict(TotSlopeReg), col = "purple", lwd = 2)
```

```
    # Calculate slope as line between two points
    #maxflow[k,7] = (maxflow[k,3]-Baseflow)/(BaseDay-PeakDay)
    #plot(dat.sub$Date, dat.sub$Mod_PH_Q_cms, type = "line", main = paste(years[k]),
     #    ylab = "Discharge (cms)", xlab = NA)
    #points(TotSlopeDate, TotSlopeQ, pch = 19, col = "violet")
    #QPoints = c(maxflow[k,3],Baseflow)
    #TotDayPts =c(PeakDate, BaseDate)
    #DayPoints = as.Date(TotDayPts, "%Y-%m-%d")
    #lines(DayPoints, QPoints, col = "purple", lwd = 2)


    # Calculate the recession slope from the peak to bankfull flow as the best fit line
    if (is.na(maxflow[k,4])) {
      maxflow[k,10] = NA #Calculate slope of highest peak lower than bankfull to baseflow
    }
    else {

    # Calculate recession slope based on best fit regression line between all points
    PeakSlopeQ = dat.sub$Mod_PH_Q_cms[dat.sub$yday %in% c(PeakDay:BF_endDay)]
    PeakSlopeDate = dat.sub$Date[dat.sub$yday %in% c(PeakDay:BF_endDay)]
    PeakSlopeReg = lm(PeakSlopeQ ~ PeakSlopeDate)
    summary(PeakSlopeReg)
    points(PeakSlopeDate, PeakSlopeQ, pch = 20, col = "pink")
    lines(PeakSlopeDate, predict(PeakSlopeReg), col = "red", lwd = 2)
    maxflow[k,10] = -1*PeakSlopeReg$coefficients[2] #((maxflow[k,3])-
(maxflow[k,4]))/(BF_endDay-PeakDay) #SLope from peak to bankfull

    # Calculate slope as line between two points
    #maxflow[k,10] = (maxflow[k,3]-maxflow[k,4])/(BF_endDay-PeakDay)
    #points(PeakSlopeDate, PeakSlopeQ, pch = 20, col = "pink")
    #QPoints = c(maxflow[k,3],maxflow[k,4])
    #PeakDayPts =c(PeakDate, BF_end)
    #DayPoints = as.Date(PeakDayPts, "%Y-%m-%d")
    #lines(DayPoints, QPoints, col = "red", lwd = 2)
    }

    # Calculate the bankfull slope from bankfull to base flow
    if (is.na(maxflow[k,4])) {
      maxflow[k,8] = NA #Calculate slope of highest peak lower than bankfull to baseflow
    }
    else {
      # Calculate recession slope based on best fit regression line between all points
      BFSlopeQ = dat.sub$Mod_PH_Q_cms[dat.sub$yday %in% c(BF_endDay:BaseDay)]
      BFSlopeDate = dat.sub$Date[dat.sub$yday %in% c(BF_endDay:BaseDay)]
```

```
    BFSlopeReg = lm(BFSlopeQ ~ BFSlopeDate)
    summary(BFSlopeReg)
    points(BFSlopeDate, BFSlopeQ, pch = 20, col = "lightblue")
    lines(BFSlopeDate, predict(BFSlopeReg), col = "blue", lwd = 2)
    maxflow[k,8] = -1*BFSlopeReg$coefficients[2]

    # Calculate slope as line between two points
    #maxflow[k,8] = (maxflow[k,4]-Baseflow)/(BaseDay-BF_endDay)
    #points(BFSlopeDate, BFSlopeQ, pch = 20, col = "lightblue")
    #QPoints = c(maxflow[k,4],Baseflow)
    #BFDayPts =c(BF_end,BaseDate)
    #DayPoints = as.Date(BFDayPts, "%Y-%m-%d")
    #lines(DayPoints, QPoints, col = "blue", lwd = 2)

  }

  # Save year-days for duration calculations
  maxflow[k,11] = BF_startDay
  maxflow[k,12] = PeakDay
  maxflow[k,13] = BF_endDay
  maxflow[k,14] = BaseDay
  maxflow[k,15] = BF_endDay - BF_startDay # Duration Of recession Limb
  maxflow[k,16] = BaseDay - PeakDay # Duration Of recession Limb
  maxflow[k,17] = BaseFlow_Date
  maxflow[k,18] = LastDay # Last recorded day of the year

  # Cumulative days before and after bankfull
  if (is.na(BF_endDay)==FALSE) { # If there was a bankfull flow (i.e., BF_endDay is not NA)
    maxflow[k,19] = LastDay - BF_endDay  # Calculate the days since BF ended
  }
  else { # if there was no bankfull flow that year...
    maxflow[k,19] = LastDay + maxflow[k-1,19] # add the total number of days in the year to the
days since BF in the previous year
  }

  if (is.na(BF_endDay)==FALSE) { # If there was a bankfull flow (i.e., BF_endDay is not NA)
    maxflow[k,20] = BF_startDay + maxflow[k-1,19] # Days since bankfull
  }
  else {
   maxflow[k,20] = LastDay + maxflow[k-1,19]
  }
  BaseStart = min(which(dat.sub$flow.er >= Baseflow))
  maxflow[k,21] = dat.sub$yday[BaseStart]
```

```
  }
}

names(maxflow) = c("year","peakdate","flow.er","BFflow", "BF_EndDate", "enddate",
            "TotalSlope","BFslope","BF_StartDate","PeakSlope","BF_startDay",
            "PeakDay","BF_endDay","Base_endDay","BankfullDuration","RecDuration",
            "BaseFlow_Date","LastDay", "CummDaysAfterBF", "CummDaysBeforeBF",
            "Base_startDay")

#maxflow = na.omit(maxflow) # Remove missing flow
#if (is.na(maxflow[,2]) == FALSE) {}
#maxflow$peakdate = as.Date(maxflow$peakdate)
#maxflow$enddate = as.Date(maxflow$enddate)
maxflow$duration = yday(maxflow$enddate)-yday(maxflow$peakdate) # Duration Of recession
Limb

# Generate ranks (note that R ranks opposite of what is desired)
maxflow$rank = (length(maxflow$year)+1)-rank(maxflow$flow.er)
maxflow$RI = (length(maxflow$year)+1)/maxflow$rank
# Calculate excedence probablity
maxflow$exceedence = 1/maxflow$RI
#maxflow$NonBFdays = maxflow$LastDay - (maxflow$BF_endDay - maxflow$BF_startDay)
#THis does not account for days before first and last BF day that do not have BF flow
maxflow$BaseDuration = maxflow$Base_endDay - maxflow$Base_startDay #THis does not
account for days before first and last BF day that do not have BF flow

maxflow1 = maxflow[2:85,]
maxflow = maxflow[,c(1,9,2,5,6,3,4,7,10,8,20,21,22,23,26,11:19,24,25)]

setwd(savepath)
write.csv(maxflow1, file = "Maxflow1_6.29.20_Base_1.91_BestFit.csv")
write.csv(maxflow, file = "Maxflow_6.29.20_Base_1.91_BestFit.csv")

#*******************************************************
# Create plots
maxflow1$enddate = as.Date(maxflow1$enddate, format="%Y-%m-%d")
maxflow1$peakdate = as.Date(maxflow1$peakdate, format="%Y-%m-%d")

plot(flow.er ~ maxflow1$RI, maxflow1, log = 'x',
   xlab = "Recurrence Interval (years)",
   ylab = "Annual Maximum discharge (cfs)",
   main = "Flood Frequency Curve of Estimated Peak Flows")

rm(list=setdiff(ls(), c("maxflow","dat","dat.almont","dat.bc","dat.er",
```

```
                 "hydrobounds","statistics","yearstats","years","colfunc",
                 "loadpath","savepath","mod2","best.span", "Baseflow")))


##########
#
#   Recession Limb Characteristics
#
##########


hydrobounds = as.data.frame(matrix(ncol = 2, nrow = 85)) # create data frame for flow regime
characteristics
names(hydrobounds) = c("start","end") # create colums for end and start dates for bankfull
flow
#hydrobounds$start = maxflow$BF_StartDay
#hydrobounds$end = maxflow$BFdata
hydrobounds$EndDay = maxflow$BaseDay # assign the ending date
#maxflow$BF_StartDate = as.Date(maxflow$BF_StartDay)

for (k in 1:85){
 #print(k)
 years2plot = years[k] # create a list of each of the 83 years of record
 dat.sub = subset(dat.er, year%in%years2plot) # create a subset of data for the current year
 FirstDate = dat.sub$Date[1] #Set the first date of the year

 #_______________________________________________
 # Calculate cummulative annual volume of water discharged by East River
 #dat.sub$yearVol[1] = dat.sub$flow.er[1]*86400   # set initial flow volume for 1st day
 dat.sub$AnnualVol[1] = dat.sub$flow.er[1]*86400   # set initial flow volume for 1st day

 for (n in 2:length(dat.sub$Date)){ # create for loop to add consecutive Q resulting in
cumulative annual Q
   dat.sub$AnnualVol[n] =  dat.sub$AnnualVol[n-1] + dat.sub$flow.er[n]*86400 # sum each
consecutive flow volume for cummulative volume
 }

 #print(n)
 maxflow$AnnualVol[k] = dat.sub$AnnualVol[n] # assign the total ANnual volume of discharge
for each year
 dat.sub$BFVol = NA #create column for bankfull flow volume and fill with NA

 #_______________________________________________
 # Calculate cummulative volume of overbank flow discharged by the East River
```

```
  for (m in 1:length(dat.sub$Date)) {

    if (is.na(maxflow$BF_StartDate[k]) == FALSE) {
      # Set initial volume for first day above Bankful flow
    dat.sub$BFVol[which(maxflow$BF_StartDate[k]==dat.sub$Date)] =
dat.sub$flow.er[which(maxflow$BF_StartDate[k]==dat.sub$Date)]*86400   # set initial flow
volume for 1st day
    #Create indices for the start and end of bankfull flow
    BF_StartIndex = which(maxflow$BF_StartDate[k]==dat.sub$Date) # Index the row for the first
day of bankful flow begins
    BF_EndIndex = which(maxflow$BF_EndDate[k]==dat.sub$Date) #index the row for the last
day of bankful flow ends

    #Creat a loop to add cumulative volume of bankfull discharge
    for (p in BF_StartIndex+1:(BF_EndIndex-BF_StartIndex)) { # create for loop to add consecutive
Q resulting in cumulative annual Q
      #print(p)
      # Old calculations that estimates max BF volume for all days between 1st and last day of
bankfull flow. THis is an iver estimate
      dat.sub$BFVol[p] = dat.sub$BFVol[p-1] + dat.sub$flow.er[p]*86400 # sum each consecutive
flow volume for cummulative volume
      #print(dat.sub$Date[p])
      }
    maxflow$BFVol[k] = dat.sub$BFVol[p] # Assign yearly volume of flow above bankful to the
annual summary
  }
  else {
   dat.sub$BFVol[m] = NA #Assign days without bankful flow as NA values
   maxflow$BFVol[k] = NA #Assign years without bankful flow as NA values
   p=NA

  }
  }

  hydrobounds$cvol.er[k] = dat.sub$AnnualVol[length(dat.sub$AnnualVol)]
  hydrobounds$BFVol[k] = dat.sub$BFVol[max(which(is.na(dat.sub$BFVol) == FALSE))]

  ### Model peaks and valleys

  baseflowinitial = mean(dat.sub$flow.er[dat.sub$month %in% list("1","2")]) # Set initial
baseflow conditions as the mean of flow in Jan and Feb
  baseflowend = mean(dat.sub$flow.er[dat.sub$month %in% list("12")]) # Set ending baseflow
conditions as the mean flow in Dec
```

```
  #create column index for the peaks defined by a rise in flow followed by a decline in flow
ocurring in three consecutive days
  peaks = which(diff(sign(diff(dat.sub$flow.er)))==-2)+1
  #create column index for the valleys defined by a decrease in flow followed by an increase in
flow ocurring in three consecutive days
  valleys = which(diff(sign(diff(dat.sub$flow.er)))==2)+1

  peakbase = dat.sub$flow.er[peaks]-baseflowinitial
  #print(peakbase)
  valleybase = dat.sub$flow.er[valleys] - baseflowinitial
  hydrographstart = 1 # Define HYDRGRAPHSTART

  for (n in 1:length(peakbase)){
    if (length(valleys) < 1){
      hydrographstart = peaks[n]
      peaks[n]
      break
    }

    if(peakbase[n] > 40){ # Check if threshold was met
      if (peaks[n] < valleys[1])  { # Check if first peak is greater than threshold
        hydrographstart = peaks[n]
        break
        }
      else {
        firstvalley = max(valleys[valleys<peaks[n]])
        }

        hydrographstart = firstvalley
        break
      }
  }

  bankfullflow = dat.sub$flow.er[dat.sub$flow.er > 8]
  maxflow$bankfullvol[k] = sum((bankfullflow)*86400) # sum the volume of water exceeding
bankfull flow
  maxflow$bankfulldays[k] = length(bankfullflow)
  hydrobounds[k,1] = hydrographstart
  BaseDays = dat.sub$flow.er[dat.sub$flow.er > Baseflow]
  maxflow$BaseflowDays[k] = length(BaseDays)
  maxflow$NonBFdays[k] = maxflow$LastDay[k] - maxflow$bankfulldays[k]

  if (k%%10 == 0){
```

```
  }
  hydrobounds$startdate[k] = as.character(dat.sub$Date[hydrobounds$start[k]])

}

# Write csv file of the temporary dat.sub datasheets for each year
#setwd(savepath)
write.csv(maxflow, "AnnualStats_6.29.20_Base_1.91_BestFit.csv", row.names = TRUE)

rm(list=setdiff(ls(), c("maxflow","dat","dat.almont","dat.bc","dat.er",
                "hydrobounds","statistics","yearstats","years","colfunc",
                "loadpath","savepath","mod2", "best.span")))

#### Extract Local Peaks above a specific flow rate above "bankfull"
#library("signal", lib.loc="~/R/win-library/3.2")
library("signal")

# Estimated bankkfull at 8 cms

for (k in 1:85){
  years2plot = years[k]
  dat.sub = subset(dat.er,year == years2plot)
  x1 = dat.sub$flow.er
  x1
  y1 = dat.sub$day

  #myfilter = butter(1, .2, type = 'low', plane='z')
  myfilter2 = filter(filt = sgolay(p = 12, n = 23), x = x1) # PEak FIlter started at 11
  #myfilter3 = fftfilt(rep(1, 10)/10, x1, n = 365)
  myfilter4 = filter(filt = sgolay(p = 7, n = 15), x = x1) # p = 5, n = 17 # 10 & 15 Oct 2017 # VALLEY
filter good as it gets

  #yfiltered = as.matrix(filter(myfilter, x1)) # apply filter
  yfiltered = myfilter2
  zfiltered = myfilter4
  ##print("**************************************************")
  ##print(years2plot)
  plot(dat.sub$flow.er,type = "n", main = paste(years2plot))
  lines(yfiltered,col = "red")
  lines(dat.sub$flow.er)
  points(dat.sub$flow.er)

  #points(yfiltered[peaks]~dat.sub$day[peaks], pch = 19)
```

```
 # PEaks
 peaks = which(diff(sign(diff(yfiltered)))==-2)+1 #identify the peaks by setting a threshold
where the next point decresaes by 2
 ##print(peaks)
 points(yfiltered[peaks]~dat.sub$yday[peaks], pch = 20, col = "orange")
 peaks2keep = (peaks[yfiltered[peaks] > 8])
 ##print("peaks 2 keep")
 ##print(length(peaks2keep))
 #SortPeaks <- peaks2keep[order(dat.sub$flow.er)]
 ###print(SortPeaks)
 ##print(peaks2keep)
 points(yfiltered[peaks2keep]~dat.sub$yday[peaks2keep], pch = 19, col = "red")

 # Valleys
 valleys = which(diff(sign(diff(zfiltered)))==2)+1 #identify the trophs by setting a threshold
where the next point incresaes by 2
 print("valleys")
 print(valleys)
 points(zfiltered[valleys]~dat.sub$yday[valleys], pch = 20, col = "green")
 valleys2keep = (valleys[zfiltered[valleys] < 100])
 print("valleys2keep")
 print(valleys2keep)
 points(zfiltered[valleys2keep]~dat.sub$yday[valleys2keep], pch = 19, col = "blue")

 #PeakFlows = yfiltered(dat.sub$flow.er[peaks2keep])

 truepeak = c()
 truepeak[1] = tail(which(dat.sub$flow.er == maxflow$flow.er[k]), n=1) # FInd the date of the
max flow and assign to peak flow
 ###print(truepeak)

 RealPeaks = c()
 leftthresh = c()
 rightthresh = c()
 PeakCount = 1
 #NotPeak = 0
 p = 0
 Rp = 0
 IsPeak = c()

 for (n in 1:length(peaks2keep)) {

   if (length(peaks2keep) == 0){ # If no peaks exceed bankfull...
```

```
      #truepeak = yday(maxflow$peakdate[k]) #Determine julian day of max peakflow if below
bankfull
      ###print(peaks2keep)
      PeakCount = 0
      ##print(PeakCount)
      break
    }



    IsPeak[n] = "N"
    leftthresh[n] = max(valleys2keep[valleys2keep < peaks2keep[n]]) # identify the valley
immediately before each peak above bankfull
    rightthresh[n] = min(valleys2keep[valleys2keep > peaks2keep[n]]) # identify the valley
immediately after each peack aboe bankfull
    p=p+1

    ##print(valleys2keep)
    ##print(leftthresh[n])
    ##print(peaks2keep[n])
    ##print(rightthresh[n])
    ##print(years[k])
    ##print(leftthresh[n])
    ##print(dat.sub$flow.er[leftthresh[n]])
    ##print(peaks2keep[n])
    ##print(dat.sub$flow.er[peaks2keep[n]])
    ##print(rightthresh[n])
    ##print(dat.sub$flow.er[rightthresh[n]])
    #if (abs(yfiltered[peaks2keep[n]]-yfiltered[leftthresh[n]]) < 5 |  # was <50 eliminates
    #   abs(yfiltered[peaks2keep[n]]-yfiltered[rightthresh[n]]) < 4){   # was <50
    #q = 0
    if (
      ((dat.sub$flow.er[peaks2keep[n]] - dat.sub$flow.er[leftthresh[n]]) > 2)
        &  # peaks that are  >2 cms from valey to left
      (dat.sub$flow.er[peaks2keep[n]] - dat.sub$flow.er[rightthresh[n]]) > 2 & # peaks that are
>2 cms from valey to right
      ((dat.sub$flow.er[rightthresh[n]]) < 10 | (dat.sub$flow.er[leftthresh[n]]) < 10) &
      #(n < length(peaks2keep) & peaks2keep[n+1] < rightthresh[n]) |
      if (n > 1) {
        TRUE
        if (peaks2keep[n-1] < leftthresh[n]) {
          TRUE
          }
          else {
            FALSE
```

```
        #IsPeak[n] = "N"
        }
      } else {TRUE} #JUst changed this from FALSE to TRUE
     )
   {
      truepeak[n] = leftthresh[n]-1+tail(which(dat.sub$flow.er[leftthresh[n]:rightthresh[n]] ==
max(dat.sub$flow.er[leftthresh[n]:rightthresh[n]])),n=1)
      Rp = Rp + 1
      RealPeaks[Rp] = peaks2keep[n]
      IsPeak[n] = "Y"
      #print("1st check _____________________________________")
      #print(peaks2keep[n])
      #print(IsPeak[n])
      ##print(p)
      ##print("1st Peaks to keep")
      ##print(peaks2keep[n])
      ##print(dat.sub$flow.er[peaks2keep[n]])
      ##print(rightthresh[n])
      ##print(dat.sub$flow.er[rightthresh[n]])
      ##print("Real peaks")
      ##print(length(RealPeaks))
      ##print(RealPeaks)
      ##print(RealPeaks[p])
      ##print(peaks2keep[n-1])
      ##print(RealPeaks[p-1])
      }

   else {
    ##print("Length of peaks 2 keep")
    ##print(length(peaks2keep))
    ##print("RealPeaks")
    ##print(length(RealPeaks))
    IsPeak[n] = "N"

   if (length(peaks2keep) == 2 & n == 1) { #length(RealPeaks == 0)) {
    #Rp = Rp + 1
    RealPeaks[1] = peaks2keep[n]
    IsPeak[n] = "Y"
    Rp = Rp + 1
    RealPeaks[Rp] = peaks2keep[n]
    ##print(length(RealPeaks))
    ##print("conditional met")
    ##print(length(RealPeaks))
    #print("3rd check_____________________________________")
```

```
    #print(peaks2keep[n])
    #print(IsPeak[n])
   } else {

   #Check all but the last and first point for issues
   if ((n > 1) & (n < length(peaks2keep))) { # NEED TO CORRECT THIS LINE
    ##print("checking small cluster peaks")
    #print("4th check________________________________________")
    #print(peaks2keep[n])
    #print(IsPeak[n])
    IsPeak[n] = "N"
    #TRUE

   if(
    (((dat.sub$flow.er[peaks2keep[n]] - dat.sub$flow.er[rightthresh[n]]) > 2) &
     (((dat.sub$flow.er[peaks2keep[n]] - dat.sub$flow.er[leftthresh[n]]) < 2))# |
      #(dat.sub$flow.er[leftthresh[n]] > 10))
      &
     ((IsPeak[n-1] == "N") &
      (dat.sub$flow.er[leftthresh[n]] < 10 | dat.sub$flow.er[leftthresh[n-1]] < 10 )))  |

    (((dat.sub$flow.er[peaks2keep[n]] - dat.sub$flow.er[rightthresh[n]]) < 2) &
     (((dat.sub$flow.er[peaks2keep[n]] - dat.sub$flow.er[leftthresh[n]]) > 2)) &
     (dat.sub$flow.er[leftthresh[n]] < 10) &
    (leftthresh[n] > peaks2keep[n-1] | IsPeak[n-1] == "N") &
    rightthresh[n] < peaks2keep[n+1])
     #& (IsPeak[n-1] == "N")
     # THis creates an error because there is no value when there is no peak detected
    )
    {
    #TRUE
    truepeak[n] = leftthresh[n]-1+tail(which(dat.sub$flow.er[leftthresh[n]:rightthresh[n]] ==
max(dat.sub$flow.er[leftthresh[n]:rightthresh[n]])), n=1)
    Rp = Rp + 1
    RealPeaks[Rp] = peaks2keep[n]
    IsPeak[n] = "Y"
    #print("5th check ________________________________________")
    #print(peaks2keep[n])
    #print(IsPeak[n])
    ##print(Rp)
    ##print("2nd Peaks to keep")
    ##print(peaks2keep)
    ##print(peaks2keep[n])
    ##print(peaks2keep[n-1])
```

```
    ##print(dat.sub$flow.er[peaks2keep[n]])
    ##print(rightthresh[n])
    ##print(dat.sub$flow.er[leftthresh[n]])
    ##print(dat.sub$flow.er[peaks2keep[n]])
    ##print("Real peaks")
    ##print(length(RealPeaks))
    ##print(RealPeaks) # Results in NA with no detected peak
    ##print(RealPeaks[Rp])
    ##print(RealPeaks[Rp-1])

   }

   } else {
   IsPeak[n] = "N"
   #print("6th check________________________________________")
   #print(peaks2keep[n])
   #print(IsPeak[n])

   }

   #Check last point and first point for discrepencies
    if (n == length(peaks2keep)) {
     #print("8th check________________________________________")
     #print(peaks2keep[n])
     IsPeak[n] = "N"
     #print(IsPeak[n])
     TRUE

     if(  ((dat.sub$flow.er[peaks2keep[n]] - dat.sub$flow.er[leftthresh[n]]) > 2 &
          (dat.sub$flow.er[peaks2keep[n]] - dat.sub$flow.er[rightthresh[n]]) > 1 & # peaks that
are >2 cms from valey to right
          (dat.sub$flow.er[leftthresh[n]]) < 10 &
          leftthresh[n] > peaks2keep[n-1]) |

       (((dat.sub$flow.er[peaks2keep[n]] - dat.sub$flow.er[rightthresh[n]]) > 2) &
        (((dat.sub$flow.er[peaks2keep[n]] - dat.sub$flow.er[leftthresh[n]]) < 2)) &
        #(IsPeak[n-1] == "N"|
         (leftthresh[n] != rightthresh[n-1]))  #|

       #(((dat.sub$flow.er[peaks2keep[n]] - dat.sub$flow.er[rightthresh[n]]) < 2) &
       # (((dat.sub$flow.er[peaks2keep[n]] - dat.sub$flow.er[leftthresh[n]]) > 2)) &
       # (dat.sub$flow.er[leftthresh[n]] < 10))# &
       # leftthresh[n] > peaks2keep[n-1] &
        #rightthresh[n] < peaks2keep[n+1])
```

```
      )
      {
        TRUE
        truepeak[n] = leftthresh[n]-1+tail(which(dat.sub$flow.er[leftthresh[n]:rightthresh[n]] ==
max(dat.sub$flow.er[leftthresh[n]:rightthresh[n]])), n=1)
        Rp = Rp + 1
        RealPeaks[Rp] = peaks2keep[n]
        IsPeak[n] = "Y"
        #print("9th check ________________________________________")
        #print(peaks2keep[n])
        #print(IsPeak[n])
      }

    } else {
      FALSE
      if (n == 1) {
        #print("10th check ________________________________________")
        #print(peaks2keep[n])
        #print(IsPeak[n])
        ##print(dat.sub$flow.er[peaks2keep[n]])
        ##print(dat.sub$flow.er[rightthresh[n]])
        TRUE


        if ((dat.sub$flow.er[peaks2keep[n]] - dat.sub$flow.er[rightthresh[n]]) > 2 &
            (dat.sub$flow.er[peaks2keep[n]] - dat.sub$flow.er[leftthresh[n]]) > 2 &
            dat.sub$flow.er[leftthresh[n]] < 10 &
            dat.sub$flow.er[rightthresh[n]] < 10 &
            rightthresh[n] < peaks2keep[n+1]) {
          TRUE
          IsPeak[n] = "Y"
          Rp = Rp + 1
          RealPeaks[Rp] = peaks2keep[n]
          #print("11th check________________________________________")
          #print(peaks2keep[n])
          #print(IsPeak[n])
        }
      }
    }

  }
  }
  if (length(RealPeaks) == 0 & length(peaks2keep) != 0) {
    #TRUE
```

```
      RealPeaks[1] = 1
    }
    PeakCount = length(RealPeaks) #PeakCount + p
    ##print("PeakCount")
    ##print(PeakCount)
  }

  truepeak = na.omit(truepeak)
  ##print(truepeak)
  ##print(peaks2keep)
  #points(dat.sub$flow.er[truepeak]~dat.sub$day[truepeak], pch = 19)
  #points(yfiltered[valleys]~dat.sub$day[valleys], pch = 19, col = "blue")

  #hydrobounds$peak[k] = length(truepeak)
  hydrobounds$peak[k] = PeakCount
  bankfullflow = dat.sub$flow.er[dat.sub$flow.er > 8] # define bankfull flow threshold
  hydrobounds$bankfullvol[k] = sum((bankfullflow)*86400) # sum the volume of water
exceeding bankfull flow
  hydrobounds$bankfulldays[k] = length(bankfullflow)

}


yearstats = cbind(maxflow[,-c(4,5)],hydrobounds[,-c(1,2)],statistics[,-1])
# You will have to rename the headers in excel unless I get some time to go back and clean
things up a bit

#setwd(savepath)
write.csv(yearstats,"YearlyStatistics_6.29.20_Base_1.91_BestFit.csv")


rm(list=setdiff(ls(), c("maxflow","dat","dat.almont","dat.bc","dat.er",
                "hydrobounds","statistics","yearstats","years","colfunc",
                "loadpath","savepath","mod2", "best.span")))


# This code will average variables for periods between imagery along the East River

# Author: Nicholas A. Sutfin
# Date: April 2020

library("plyr")
#library("smwrBase", lib.loc="~/R/win-library/3.2")
library("lattice") #, lib.loc="C:/Program Files/R/R-3.3.0/library")
```

```
library("lubridate")
library("hydroGOF")

# User space same as save path from steps 1-4
savepath = '/Users/NicholasSutfin/Documents/EastRiver/ER_Rcode/Baseflow_1.91_BestFit/' # Calculating slope as line between 1st and last points (2p)
setwd(savepath)
# Load ALmont data for 2015-2017 as csv file, convert to SI units, code the date as a date, and define the year
#Alm_Q <- read.csv("ER_AlmQ_2015-2017.csv", header=TRUE)
AnnualStats <- read.csv("YearlyStatistics_6.29.20_Base_1.91_BestFit.csv", header=TRUE)
AnnualStats$period = NA

for (i in 2:length(AnnualStats$year)) {
 #AnnualStats$TimeSinceBF[i] = AnnualStats$BF_startDay[i] + AnnualStats$DaysSinceBF[i-1]
 if (AnnualStats$year[i] < 1955){
  AnnualStats$period[i] = "before1955"
 }
 if (AnnualStats$year[i] > 1954 & AnnualStats$year[i] < 1974){
  AnnualStats$period[i] = "1955to1973"
 }
 if (AnnualStats$year[i] > 1973 & AnnualStats$year[i] < 1984){
  AnnualStats$period[i] = "1974to1983"
 }
 if (AnnualStats$year[i] > 1983 & AnnualStats$year[i] < 1991){
  AnnualStats$period[i] = "1984to1990"
 }
 if (AnnualStats$year[i] > 1990 & AnnualStats$year[i] < 2002){
  AnnualStats$period[i] = "1991to2001"
 }
 if (AnnualStats$year[i] > 2001 & AnnualStats$year[i] < 2012){
  AnnualStats$period[i] = "2002to2011"
 }
 if (AnnualStats$year[i] > 2011 & AnnualStats$year[i] < 2016){
  AnnualStats$period[i] = "2012to2015"
 }
 if (AnnualStats$year[i] > 2015){
  AnnualStats$period[i] = "after2015"
 }
}

#na.rm(AnnualStats)

DecadalStats = ddply(AnnualStats, ~period, summarise,
```

```
            MeanPeakDay = mean(PeakDay),
            MeanPeakQ = mean(flow.er), MaxPeakQ = max(flow.er),
            MeanBFDuration = mean(BankfullDuration, na.rm=TRUE), MaxBFDuration =
max(BankfullDuration, na.rm=TRUE),
            MeanBFDays = mean(bankfulldays, na.rm=TRUE), MaxBFDays = max(bankfulldays,
na.rm=TRUE),
            MeanBaseDuration = mean(BaseDuration, na.rm=TRUE), MaxBaseDuration =
max(BaseDuration, na.rm=TRUE),
            MeanBaseDays = mean(BaseflowDays, na.rm=TRUE), MaxBaseDays =
max(BaseflowDays, na.rm=TRUE),
            MeanDaysAfterBF = mean(CummDaysAfterBF, na.rm=TRUE), MaxDaysAfterBF =
max(CummDaysAfterBF),
            MeanDaysB4_BF = mean(CummDaysBeforeBF, na.rm=TRUE), MaxDaysB4_BF =
max(CummDaysBeforeBF, na.rm=TRUE),
            MeanNonBFdays = mean(NonBFdays, na.rm=TRUE), MaxNonBFdays =
max(NonBFdays, na.rm=TRUE),
            MeanBaseDay = mean(Base_endDay, na.rm=TRUE), MeanBF_EndDay =
mean(BF_endDay, na.rm=TRUE),
            MeanPeaks = mean(peak, na.rm=TRUE), MaxPeaks = max(peak, na.rm=TRUE),
            MeanTotSlope = mean(TotalSlope, na.rm=TRUE), MaxTotSlope = max(TotalSlope,
na.rm=TRUE),
            MeanBFSlope = mean(BFslope, na.rm=TRUE), MaxBFSlope = max(BFslope,
na.rm=TRUE),
            MeanPeakSlope = mean(PeakSlope, na.rm=TRUE), MaxPeakSlope = max(PeakSlope,
na.rm=TRUE),
            MeanAnnualVol = mean(AnnualVol), MaxAnnualVol = max(AnnualVol),
TotAnnualVol = sum(AnnualVol),
            # ALtered 6.26.2020 to include volume for days above BF rather than all days
between first and last BF days
            MeanBFVol = mean(bankfullvol,na.rm=TRUE), MaxBFVol =
max(bankfullvol,na.rm=TRUE),
            TotBFDuration = sum(BankfullDuration, na.rm=TRUE), TotBaseDuration =
sum(BaseDuration, na.rm=TRUE),
            TotNonBFdays = sum(NonBFdays, na.rm=TRUE), TotBF_EndDay = sum(BF_endDay,
na.rm=TRUE),
            TotDaysB4_BF = sum(CummDaysBeforeBF, na.rm=TRUE), TotDaysAfterBF =
sum(CummDaysAfterBF),
            TotBFVol = sum(BFVol, na.rm=TRUE))

#setwd(savepath)
write.csv(DecadalStats, "TimePeriodStats_6.29.20_1.91_BestFit.csv", row.names = TRUE)

# This code will examine 15 min hydrograph datasets from the ALmont gage and East RIver
study site
```

```
# to quantify fluctuations above and below bankfull along the recession limb

# Author: Nicholas A. Sutfin
# Date: Oct. 18th 2017

# This code will examine to hydrograph dataset, select matching days
# and times and conduct a regression that can be used to fill in missing data
# Author: Nicholas A. Sutfin
# Date: Oct. 18th 2017

library(plyr)
library(chron)
library(tidyr)
#library(smwrBase, lib.loc=~/R/win-library/3.2)
library(lattice) #, lib.loc=C:/Program Files/R/R-3.3.0/library)
library(lubridate)
library(hydroGOF)
library(OHLCMerge)
library(corrplot)
library(lmtest)
library(car)
library(MASS)
library(Hmisc)

# Set user space on LANL PC
loadpath = '/Users/NicholasSutfin/Documents/EastRiver/ER_Rcode'
savepath = '/Users/NicholasSutfin/Documents/EastRiver/ER_Rcode'
setwd(loadpath)
#setwd("/Users/306722/Documents/EastRiver/ER_Rcode")

# Load ALmont data for 2015-2017 as csv file, convert to SI units, code the date as a date, and
define the year
Alm_15Q <- read.csv("Almont_30minQ_1987_2020.csv", header=TRUE) #load USGS discharge
data
Alm_15Q$Discharge_cfs =
as.numeric(levels(Alm_15Q$Discharge_cfs))[Alm_15Q$Discharge_cfs] # convert Q factors to
numeric values
which(is.na(Alm_15Q$Discharge_cfs) == TRUE) #Check for NA values
Alm_15Q$AlmQ_cms = Alm_15Q$Discharge_cfs*0.0283168 # Calulate Q conversion from cfs to
cms
which(is.na(Alm_15Q$Discharge_cfs) == TRUE) # check for NA values after numeric conversion

Alm_15Q$date = as.Date(Alm_15Q$date, format="%m/%d/%y") # convert Q factors to numeric
values
```

```
Alm_15Q$DaTime = paste(Alm_15Q$date, Alm_15Q$time)
Alm_15Q$DateTime = as.POSIXct(Alm_15Q$DaTime, format = "%Y-%m-%d %H:%M")
Alm_15Q$year = year(Alm_15Q$Date)
Alm_15Q$month = month(Alm_15Q$Date)
Alm_15Q$Calday = day(Alm_15Q$Date)
Alm_15Q$Yday = yday(Alm_15Q$Date)
#Alm_15Q$Yday = yday(Alm_15Q$Date)
Alm_15Q = as.data.frame(Alm_15Q)
#______________________________________________________________________
# Load Pump house data for 2015-2017 as csv file, convert to SI units, code the date as a date,
and define the year
PH_10Q <- read.csv("PHQ_2014_2018.csv", header=TRUE)
#PH_10Q <- read.csv("PH_10Q.csv", header=TRUE) #load East RIver pump house discharge data
PH_10Q$DateTime = as.POSIXct(PH_10Q$date, format = "%m/%d/%y %H:%M")
PH_10Q$year = year(PH_10Q$DateTime)
PH_10Q$month = month(PH_10Q$DateTime)
PH_10Q$Calday = day(PH_10Q$DateTime)
PH_10Q$Time = format(as.POSIXct(strptime(PH_10Q$DateTime, "%Y-%m-%d %H:%M",tz=""))
,format = "%H:%M")
PH_10Q$Yday = yday(PH_10Q$DateTime)
PH_10Q = as.data.frame(PH_10Q)
#plot(PH_10Q$DateTime, PH_10Q$PHQ_cms, type = "l", col = "blue")

#______________________________________________________________________
# Find matching date-time combinations and create new dataset
#PH_Q_match =
Alm_15Qnew1  = Alm_15Q[,c(4,6,7,8,9,2,10)][!duplicated(Alm_15Q$DateTime),]
Alm_15Qnew = Alm_15Qnew1[which(is.na(Alm_15Qnew1$DateTime) == FALSE),]
PH_10Qnew  = PH_10Q[,c(2:8)]

Q_int <- intersect.POSIXct(PH_10Qnew$DateTime, Alm_15Qnew$DateTime)
Alm_Q_match <- Alm_15Qnew[Alm_15Qnew$DateTime %in% Q_int, ] #Alm_15Q[Q_int, ] #
PH_Q_match <- PH_10Qnew[PH_10Qnew$DateTime %in% Q_int, ] #PH_10Q[Q_int, ] #
Q_diff <- setdiff(PH_Q_match$DateTime, Alm_Q_match$DateTime)
#which(PH_Q_match$DateTime == NA)
#which(Alm_Q_match$DateTime == NA)
All_Qmatch <- cbind(Alm_Q_match, PH_Q_match)

# Create a smaller zoomed in plot to view Q around Bankfull Q (8 cms)
plot(All_Qmatch$DateTime, All_Qmatch$PHQ_cms, type = "l",
   ylim = c(5,10), xlab = "Day of Year", ylab = "Discharge (cms)", lwd = 1, main = "East River 2015
recession")

# Plot discharge data
```

```
plot(All_Qmatch$DateTime, All_Qmatch$AlmQ_cms, col = "blue", type = "l")
lines(All_Qmatch$DateTime, All_Qmatch$PHQ_cms, col = "royalblue", type = "l")
#____________________________________________________________
# Linear regression between the Almont and PH gauges 2014-2016

Qreg <- lm(All_Qmatch$PHQ_cms ~ All_Qmatch$AlmQ_cms, data = All_Qmatch)
summary(Qreg)
Qreg # adjusted R squared = 0.95
# For all days: PHQ = -0.081804 + 0.211284(Alm)
# Excluding frozen days, regression output: PHQ = 0.010948 + 0.211611(Alm)

par(mfrow=c(1,1), mar=c(4,4,2,2), cex = 1, lwd = 1)
plot(All_Qmatch$AlmQ_cms, All_Qmatch$PHQ_cms, col = "blue",
    xlab = "Discharge at Almont (cms)", ylab = "Discharge at Study Site (cms)")
lines(All_Qmatch$AlmQ_cms, Qreg$coefficients[1] +
Qreg$coefficients[2]*All_Qmatch$AlmQ_cms,
     col = "black")
par(cex = 0.6)
#points(All_Qmatch$AlmQ_cms, All_Qmatch$PHQ_cms, pch = 19, col = "red")
text(10, 15, expression("r"^{2} ~"= 0.94"), cex = 1.5)

# Use regression to extend daily Q for PH based on Almont flow
#____________________________________________________________________________
____
# regression output: PHQ = -0.081804 + 0.211284(Alm)

# Reduce Almont Data size
Alm_15Q_sel = Alm_15Qnew[((Alm_15Qnew$time == "0:00") | (Alm_15Qnew$time == "1:00")
| (Alm_15Qnew$time == "2:00") |
                    (Alm_15Qnew$time == "3:00") |(Alm_15Qnew$time == "4:00") |
(Alm_15Qnew$time == "5:00") |
                    (Alm_15Qnew$time == "6:00") |(Alm_15Qnew$time == "7:00") |
(Alm_15Qnew$time == "8:00") |
                    (Alm_15Qnew$time == "9:00") |(Alm_15Qnew$time == "10:00") |
(Alm_15Qnew$time == "11:00") |
                    (Alm_15Qnew$time == "12:00") |(Alm_15Qnew$time == "13:00") |
(Alm_15Qnew$time == "14:00") |
                    (Alm_15Qnew$time == "15:00") | (Alm_15Qnew$time == "16:00") |
(Alm_15Qnew$time == "17:00") |
                    (Alm_15Qnew$time == "18:00") | (Alm_15Qnew$time == "19:00") |
(Alm_15Qnew$time == "20:00") |
                    (Alm_15Qnew$time == "21:00") | (Alm_15Qnew$time == "22:00") |
(Alm_15Qnew$time == "23:00") |
                    (Alm_15Qnew$time == "24:00")), ]
```

```
All_Q_1987_2020 = Alm_15Q_sel[which(is.na(Alm_15Q_sel$AlmQ_cms) == FALSE), ] #[
,c(6,1,7:9,2,10,4)]
All_Q_1987_2020$Mod_PHQ_cms = Qreg$coefficients[1] +
Qreg$coefficients[2]*All_Q_1987_2020$AlmQ_cms

# Plot a zoomed in window of the recession limb for 2017
Flow2017 = All_Q_1987_2020[All_Q_1987_2020$year == 2017,]
Recession2017 = Flow2017[Flow2017$month == 6,]
Recession2017 = Recession2017[Recession2017$Calday > 6,]
DailyQ = ddply(Recession2017, ~Yday, summarise,
          MeanQ = median(Mod_PHQ_cms),
          DateTime = min(DateTime))

Rmax = max(Recession2017$DateTime)
Rmin = min(Recession2017$DateTime)
window1 <- data.frame(xmin=Rmin, xmax=Rmax, ymin=8, ymax=11)
window2 <- data.frame(xmin=Rmin, xmax=Rmax, ymin=5, ymax=12)


ggplot(data=Recession2017, aes(x=DateTime, y=Mod_PHQ_cms)) +
  geom_path() +
  geom_line(data = DailyQ, aes(x = DateTime , y = MeanQ, colour = 003399)) +
  geom_line(data=Recession2017, aes(x=DateTime, y=Mod_PHQ_cms)) +
  labs(y = expression(paste("Discharge (m"^"3", "s"^"-1",")")), x = "") +
  theme(axis.title.x = element_blank()) +
  theme(text = element_text(size=13)) +
  scale_y_continuous(minor_breaks = seq(6,16,1), breaks = seq(6,16,2)) +
  geom_rect(data=window2, aes(xmin=Rmin, xmax=Rmax, ymin=5, ymax=10), fill="blue",
alpha=0.20, inherit.aes = FALSE) +
  geom_rect(data=window1, aes(xmin=Rmin, xmax=Rmax, ymin=7.95, ymax=8.05), fill="red",
alpha=0.5, inherit.aes = FALSE)


  #geom_rect(x=x, aes(xmin=Rmin, xmax=Rmax, ymin=8, ymax=11, alpha=.5))
  #geom_density(aes(, alpha=.5))


######################################################################

######################################################################
#   Recession Limb Characteristics
######################################################################

######################################################################
```

```
years = c("1988","1989","1990","1991","1992","1993","1994","1995","1996",
        "1997","1998","1999","2000","2001","2002","2003","2004","2005",
        "2006","2007","2008","2009","2010","2011","2012","2013","2014",
        "2015","2016","2017","2018","2019")

DielYears = data.frame("Years" = years)
DielYears$PeakDate = as.POSIXlt(All_Q_1987_2020$DateTime[1], format = "%Y-%m-%d
%H:%M:%S")
par(cex = 1, mar = c(4,4,2,1))
BFmin = 5
BFmax = 10
DielFluctuation = 2

for (p in 1:length(years)) {
  DataYear = years[p]
  DielData =  subset(All_Q_1987_2020, year%in%DataYear)
  DielRec = 0
  AllDiel = 0
  DielYears$PeakFlow[p] = max(DielData$Mod_PHQ_cms[which(is.na(DielData$Mod_PHQ_cms)
== FALSE)]) #max(DielData$Mod_PHQ_cms)
  DielYears$PeakDate[p] = as.POSIXlt(DielData$DateTime[max(which(DielData$Mod_PHQ_cms
== DielYears$PeakFlow[p]))], format = "%Y-%m-%d %H:%M:%S")
  DielYears$PeakDay[p] = yday(DielYears$PeakDate[p])
  DielYears$PostPeakDays[p] = max(DielData$Yday) - DielYears$PeakDay[p]
  PeakIndex = which(DielData$DateTime == DielYears$PeakDate[p])
  DielPeaks = c()
  DielTotal = 0
  maxDiel = 0
  minDiel = 0
  #print("__________________________")
  #print(years[p])
  #print(DielPeaks)
  #print(minDiel)
  #print(maxDiel)
  #print(AllDiel)
  #print(DielRec)


  #Find unique days for the year on record
  UniqDays = unique(DielData$Yday)
  PostPeakUniq = UniqDays[UniqDays > DielYears$PeakDay[p]]
```

```
  if (DielYears$PeakFlow[p] > 6) {

    for (r in 2:length(UniqDays)) {
      # Assign daily max and min discharge values
      DailyFlow = subset(DielData, DielData$Yday == UniqDays[r])
      Dmax = max(DailyFlow$Mod_PHQ_cms)
      #DmaxIndex = which(DailyFlow$Mod_PHQ_cms == Dmax)
      Dmin = min(DailyFlow$Mod_PHQ_cms)

      if (((Dmax < BFmax) | (Dmin > BFmin)) & ((Dmax - Dmin) > DielFluctuation)) {
        AllDiel = AllDiel + 1
      }
      DielYears$AllDiel[p] = AllDiel # Record number of times Q crosses BF during the entire year
    }
    #print("----------------------")
    #print(years[p])
    #print("YES")
    for (q in 1:length(PostPeakUniq)) {
      # Assign daily max and min discharge values
      DailyFlow = subset(DielData, DielData$Yday == PostPeakUniq[q])
      Dmax = max(DailyFlow$Mod_PHQ_cms)
      #DmaxIndex = which(DailyFlow$Mod_PHQ_cms == Dmax)
      Dmin = min(DailyFlow$Mod_PHQ_cms)

      if (((Dmax < BFmax) | (Dmin > BFmin)) & ((Dmax - Dmin) > DielFluctuation)) {

        DielRec = DielRec + 1
        DielPeaks[DielRec] = DailyFlow$Yday # Index the day of year for each Q that crosses BF
after peak flow
        #print(length(DielPeaks))
        #print(DielPeaks)
        maxDiel = max(DielPeaks)
        minDiel = min(DielPeaks)
        DielRange = Dmax - Dmin
        DielTotal = DielTotal + DielRange
        DielYears$minDiel[p] = minDiel
        DielYears$maxDiel[p] = maxDiel

        # Plot portion of recession limb within bankfull window
        days = c(minDiel, maxDiel)
        Qlow = c(BFmin, BFmin)
        Qhigh = c(BFmax, BFmax)
        #plot(DielData$day, DielData$Mod_PHQ_cms, type = "l",  main = paste(years[p]),
```

```
        #ylim = c(6,10), xlim = c(DielYears$minDiel[p]-1,DielYears$maxDiel[p]+1),
        #xlab = "Day of Year", ylab = "Discharge (cms)", lwd = 1)
     #lines(c(0,250), c(8,8), col="blue")

     # plot a transparent band around the bankfull window
     #polygon(c(days, rev(days)), c(Qlow, Qhigh), border = NA,
          #col = rgb(red = 0.0, green = 0.0, blue = 0.5, alpha = 0.4))
    }
    AveDielRange = DielTotal/DielRec
    DielYears$TotalDielRange[p] = DielTotal
    DielYears$AveDielRange[p] = AveDielRange
    DielYears$DielRec[p] = DielRec # Record number of times Q crosses BF during recession limb

  }
  #plot(DielData$day, DielData$Mod_PHQ_cms, type = "l",  main = paste(years[p]),
      #xlab = "Day of Year", ylab = "Discharge (cms)", lwd = 1)
 }

 else {
  #print("----------------------")
  #print(years[p])
  #print("NO")
  DielYears$TotalDielRange[p] = NA
  DielYears$AveDielRange[p] = NA
  DielYears$DielRec[p] = NA
  DielYears$minDiel[p] = 0
  DielYears$maxDiel[p] = 0
  }
 }

DielYears

# THis data was combined with the average statistics form the hydrologic and
# imagery analysis to produce the datasheet used below

##################################################################################
####################################
# Conduct Multiple Regression to examine role of diel fluctuations on erosion
##################################################################################
####################################

# Load data on Mac with slope analysis from primary 60 year analysis derived from daily mean
data
# Set user space
```

```
savepath =
'/Users/NicholasSutfin/Documents/EastRiver/ER_Rcode/Baseflow_0.49_2p_corrected/' #
Calculating slope as line between 1st and last points (2p)
setwd(savepath)
write.csv(DielYears,"DielRecessionDate_6.30.20_2cms_>6_5_10.csv")

# Load other hydrologic variables from baoder analysis and 6 year hydro record
YearlyHydroStats <- read.csv("DielRecessionRegData_6.29.20.csv", header=TRUE)

# cbind annual hydrologic data with diel data
DielRegData = cbind(DielYears, YearlyHydroStats)

DielRegData = DielRegData[(which(is.na(DielRegData$DielRec) == FALSE)), ]

for (i in 1:length(DielRegData$Years)) {
  if (DielRegData$DielRec[i] == 0) {
    DielRegData$AveDielRange[i] = 0
  }
}

#==============================================================
#Assign variables
#RespVar = DielRegData$AveDielRange
Preds = subset(DielRegData, select = c(6:9,16:18)) #c(3:6,9:52))
Preds[, c(1:7)] <- sapply(Preds[, c(1:7)], as.numeric)

# examine subset correlations
par(mfrow=c(1,1), mar=c(3,3,3,2), cex = 1.3)
DataCorr = cor(Preds, method = "pearson")
corrplot(DataCorr)

CorrT = rcorr(as.matrix(Preds), type = "pearson")
CorrRtable = data.frame(CorrT$r)
CorrPtable = data.frame(CorrT$P)
CorrT

write.csv(CorrRtable, file = "DielData_RCorrs_6.30.20_2cms_>6_5_10.csv") # with new data
from new stats calculated June 2020
write.csv(CorrPtable, file = "DielData_PCorrs_6.30.20_2cms_>6_5_10.csv")

##################################################
# Number of Diel Fluctuations
#_______________________________________________
```

```
cor.test(Preds$TotalSlope, Preds$DielRec)
DielRecReg = lm(Preds$TotalSlope ~ Preds$DielRec, data=Preds)
summary(DielRecReg)

ggplot(Preds, aes(x=TotalSlope, y=DielRec)) +
  geom_point(color='#D55E00', size = 3) +
  geom_smooth(method=lm, color='#2C3E50', linetype="dashed") +
  theme(text = element_text(size=13)) +
  labs(title = "2cms fluctuations >6cms from 5-10cms window",
       y=expression(paste("Number of diel fluctuations > 2 m"^"3", "s"^"-1")),
       x = expression(paste("Slope of recession limb (m"^"3", "s"^"-1", "day"^"-1",")")))

################################################
# Total sum magnitude of diel fluctuation
#_______________________________________________

cor.test(Preds$TotalSlope, Preds$TotalDielRange)

ggplot(Preds, aes(x=TotalSlope, y=TotalDielRange)) +
  geom_point(color='#D55E00', size = 3) +
  geom_smooth(method=lm, color='#2C3E50', linetype="dashed") +
  theme(text = element_text(size=13)) +
  labs(title = "2cms fkuctuations >6cms from 5-10cms window",
       y=expression(paste("Summed magnitude of diel fluctuation")),
       x = expression(paste("Slope of recession limb (m"^"3", "s"^"-1", "day"^"-1",")")))

################################################
# Average magnitude of diel fluctuation
#_______________________________________________

cor.test(Preds$TotalSlope, Preds$AveDielRange)

ggplot(Preds, aes(x=TotalSlope, y=AveDielRange)) +
  geom_point(color='#D55E00', size = 3) +
  geom_smooth(method=lm, color='#2C3E50', linetype="dashed") +
  theme(text = element_text(size=13)) +
  labs(title = "2cms fkuctuations >6cms from 5-10cms window",
       y=expression(paste("Average magnitude of diel fluctuation (m"^"3","s"^"-1", ")")),
       x = expression(paste("Slope of recession limb (m"^"3", "s"^"-1", "day"^"-1",")")))
```

Supporting Information for

River bank erosion and lateral accretion linked to hydrograph recession and flood duration in a snowmelt-dominated system

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Additional Supporting Information (Files uploaded separately)

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Introduction

Figures and tables below are cited within the text of Sutfin et al. to provide supporting information and summary data. In addition, we briefly provide explanation of the statistical transformations conducted for analyses and referenced in the text.

Multiple linear regression model residuals met assumptions of homoscedasticity and normality (at the 95% confidence level) after a natural log transform of annual floodplain vertical accretion rate and boxcox power transformations with lambda (λ) exponent coefficients of 0.1010101 and 0.2626263 for the area of floodplain eroded and laterally accreted, respectively. Eroded and accreted areas appearing in equations 2 and 3 in the main text contain exponents of the reciprocal of these lambda values, necessary if one were to attempt calculation of erosion or accretion based on parameters listed in those equations.

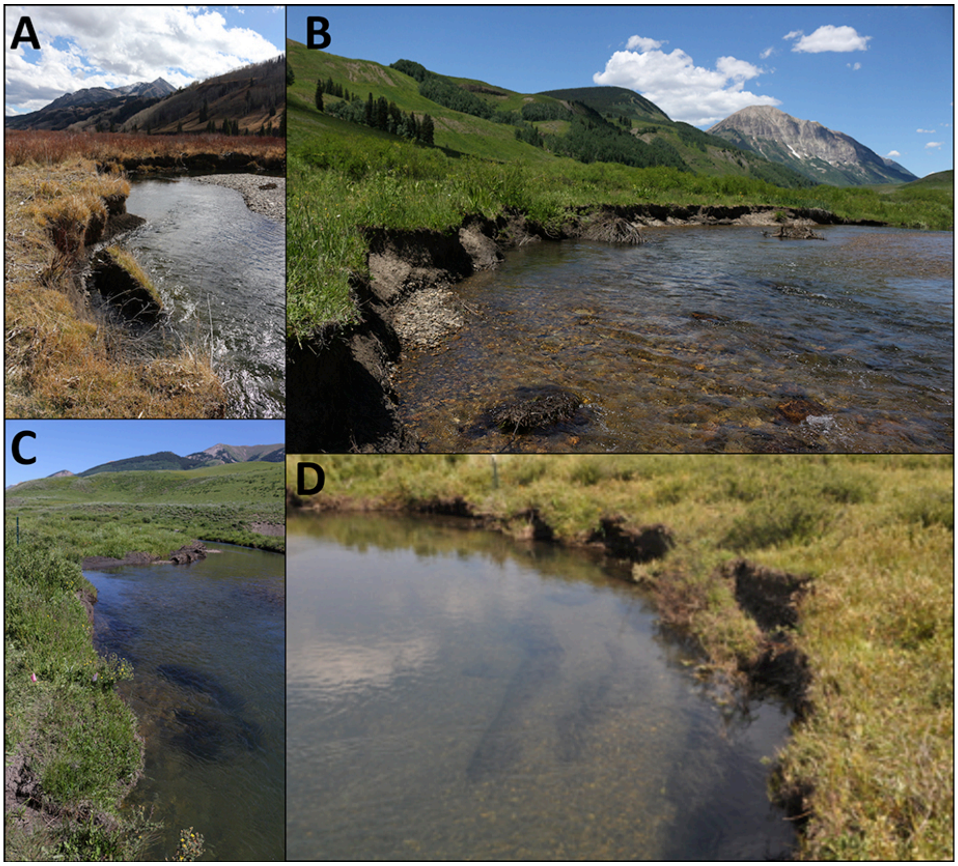

Figure S1: Bank erosion commonly observed along the East River. The upper fine-grained portion of floodplain sediment collapses in large blocks on the outside of channel bends. Following undercutting and erosion of underlying sandy gravel, channel banks crack (A, C) and eventually fall into the channel (A, B, D) where they remain on the channel bed at low flows (A, B) and can be buried by gravel during higher flows (C,D).

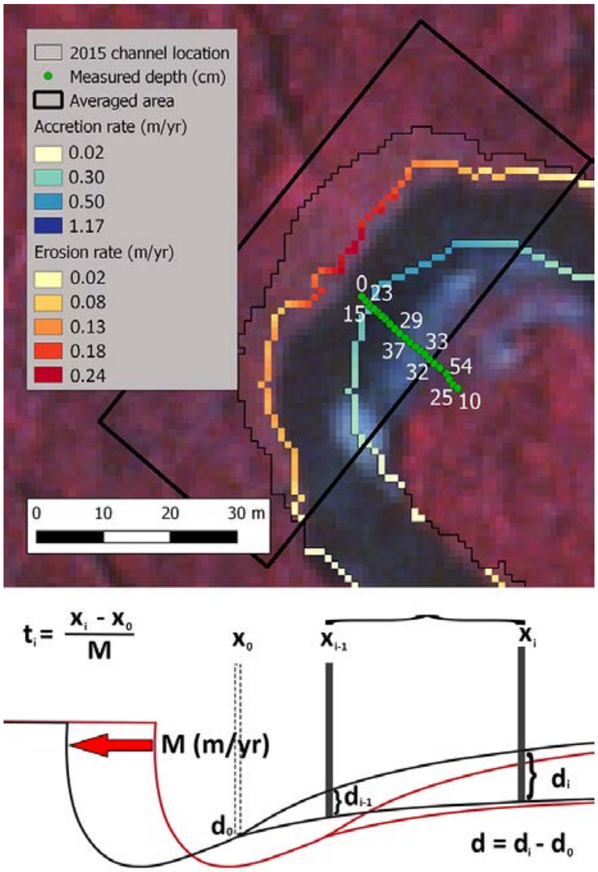

Figure S2. At each bend where a transect of measured depths was located, linear erosion rates along the bank (depicted as the outer bank in 1973 by the yellow-red spectrum) and accretion rates (depicted as the inner bank in 2015 by the yellow-blue spectrum) were averaged within a rectangle. The rectangle was drawn to capture the accreted bank pixels with a boundary defined by the approximate location where the outer bank from 1973 intersect the outer bank from 2015 (thin black line). The difference in the horizontal distances (x_i and x_{i-1}) between consecutive depth measurements (d_i and d_{i-1}) was divided by the mean migration rate to determine the duration of sediment deposition at each point (t_i). Vertical accretion rate at each point was then calculated by the difference in measured depth between consecutive points divided by the time between points. This point-by-point method was conducted in addition to that described in the main text, but yielded inconsistent results as a function of small changes in floodplain topography and possible alternative periods of point bar erosion and deposition, so this analysis was not used for the results presented.

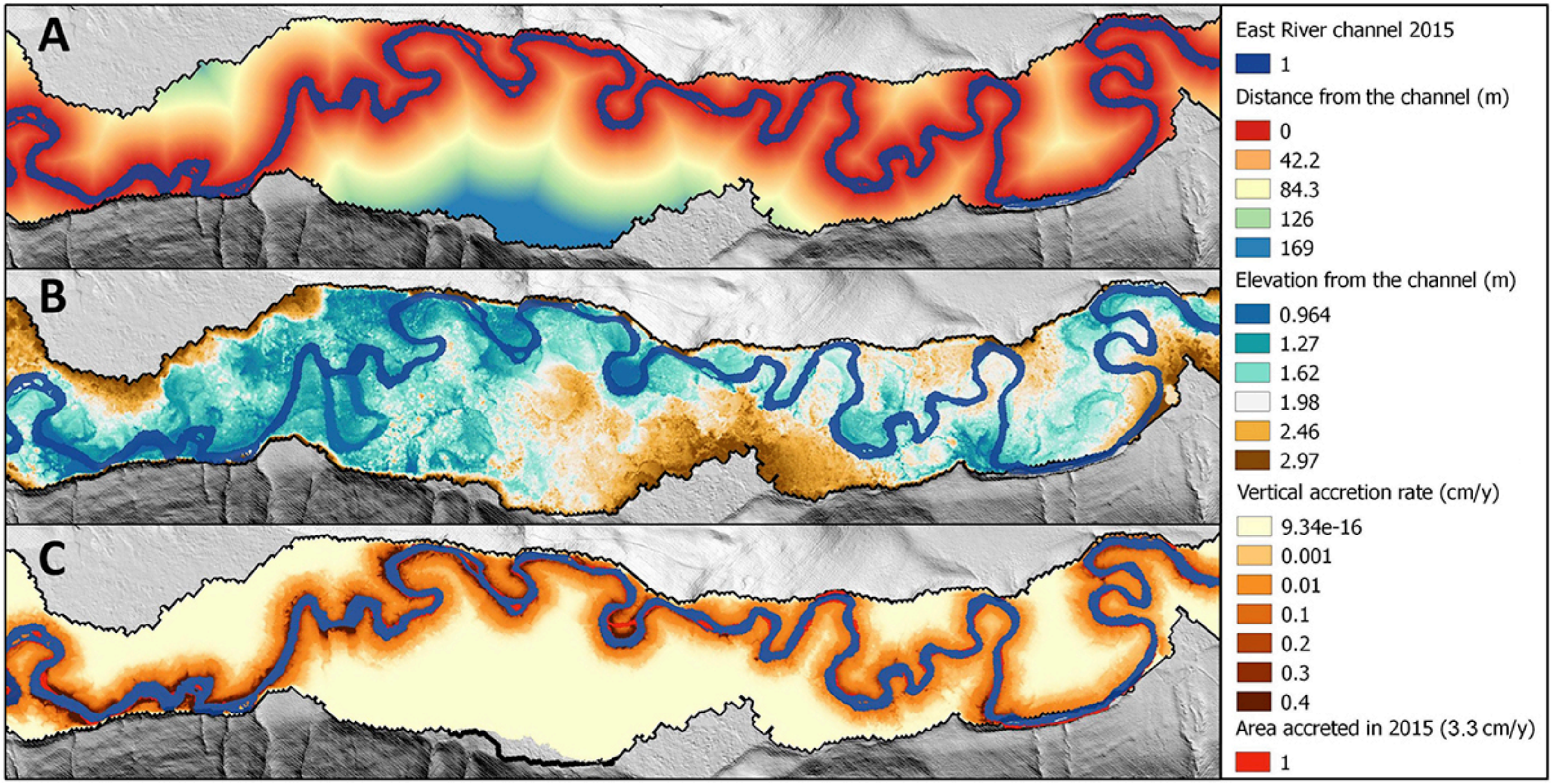

Figure S3 Example from the 2015 pixel grid calculations. Distance from the channel (A) for each time period and relative elevation (B) for all time periods were used in a multiple linear regression to estimate mean overbank vertical accretion rate (r_{va}) across the floodplain (C) using the following equation. $\ln(r_{va}) = 1.204490 - 0.072038x - 1.205276z$ where x is distance from the channel along a transects orthogonal to the channel and z is elevation from the channel. As indicated in the legend, areas in red on the vertical accretion map are those identified from SCREAM analysis from differences in channel masks in consecutive years. Long-term deposition from measured depths within 10 m from the active channel indicated a mean vertical accretion rate of 3.3 cm y^{-1}, which was applied to the area of lateral accretion. Overbank deposition outside of the red accreted areas was estimated using relationships determined in multiple regression equation 3.

TABLES

Years	Erosion	Accretion
1973-1983	17%	14%
1983-1990	25%	14%
1990-2001	16%	16%
2001-2011	19%	13%
2011-2015	41%	25%

Table S1 . Percentage error in floodplain area estimates from SCREAM, as calculated and outlined by Rowland et al. (2016). As described in the text, estimates of error for the time period between 1955 and 1973 were not obtainable through SCREAM, thus errors presented in Table 1 and Figure 3 are estimated as two times the maximum error from other time periods.

Table S2. Field and remotely sensed data for stepwise multiple linear regression of measured floodplain fine sediment depths at 315 points across 51 transects.

Table S3. Annual hydrologic indices for synthetic hydrographs at the East River study site constructed using a linear regression with the USGS East River at Almont stream gage and parameters extracted using code provided.

Variable	Floodplain vertical accretion	
	Considered	Included
Surface elevation (m)	☓	✓**
Elevation of gravel surface (m)	☓	
Distance from the channel (m)	☓	✓***
Relative elevation from the channel (m)	☓	
Duration (years)	☓	
Channel width (m)	☓	
Valley width (m)	☓	☓
Confinement (m^2/m^2)	☓	✓**
Reach valley slope (m/m)	☓	
Reach sinuosity (m)	☓	☓
Reach channel slope (m/m)	☓	
Local valley slope (m/m)	☓	
Local sinuosity (m/m)	☓	
Local Channel slope (m/m)	☓	☓
Bend orientation angle	☓	☓
Radius of curvature	☓	✓-
Inside of bend	☓	☓
Outside of bend	☓	

Table S4. Variables considered (☓) before elimination following reduction of collinearity and examined (☓) using stepwise multiple linear regression for vertical accretion. Among variables examined, those marked with (✓) indicate variables retained in the optimal multiple linear regression model. Significance of variables in the regression model is denoted at confidence levels of 99.9% ***, 99% **, 95% *, 90% . , or not significant <90% -

Variable	Floodplain area along nine reaches over 6 time periods			Entire study segment over 6 time periods		
		Examined			Examined	
	Considered	Erosion	Accretion	Considered	Erosion	Accretion
Channel slope	✗	✗	✗			
Valley Slope	✗					
Confinement	✗	✗	✗			
Mean Channel width	✗	✗	✓*			
Sinuosity	✗	✓**	✓***			
Mean Day of Peak Flow	✗		✗	✗		
Mean Peak Flow ($m^3 s^{-1}$)	✗			✗		
Max Peak Flow ($m^3 s^{-1}$)	✗			✗		
Mean Bankfull Duration (days)	✗	✗		✗		
Max Bankfull Duration (days)	✗			✗		
Mean Days Above Bankfull Flow	✗			✗		
Max Days Above Bankfull Flow	✗		✗	✗		✓.
Mean Duration Above Baseflow (days)	✗		✗	✗		
Max Duration Above Baseflow (days)	✗	✓*	✗	✗		
Mean Days Above Baseflow	✗	✗		✗		
Max Days Above Baseflow	✗		✓*	✗		
Mean Days Since Bankfull Flow	✗			✗		
Max Days Since Bankfull Flow	✗			✗		
Mean Day Baseflow Ends	✗			✗		
Mean Day Bankfull Flow Ends	✗	✗		✗		
Mean No. Peaks Above Bankfull	✗			✗		
Maximum No. Peaks Above Bankfull	✗			✗		
Mean Total Recession Slope ($m^3 s^{-1} day^{-1}$)	✗			✗		
Max Total Recession Slope ($m^3 s^{-1} day^{-1}$)	✗	✓***		✗	✓**	
Mean Bankfull Recession Slope ($m^3 s^{-1} day^{-1}$)	✗			✗		
Max Bankfull Recession Slope ($m^3 s^{-1} day^{-1}$)	✗		✓.	✗		
Mean Total Annual Volume (km^3)	✗			✗		
Max Total Annual Volume (km^3)	✗			✗		
Mean Bankfull Volume (km^3)	✗			✗		
Max Bankfull Volume (km^3)	✗	✗		✗		
Power transformation coefficient (lambda)		0.1010101	0.2626263		NA	NA
Coefficient of determination (r^2)		0.59	0.55		0.91	0.59
Regression model p-value		<0.0001	<0.0001		0.003	0.074

Table S5. Variables considered (✗) before elimination following reduction of collinearity and examined (✗) using stepwise multiple linear regression for lateral erosion and accretion. Among variables examined, those marked with (✓) indicate variables retained in the optimal multiple linear regression model. Significance of variables in the regression model is denoted at confidence levels of 99.9% ***, 99% **, 95% *, 90% . , or not significant <90% -

Table S6. Correlation matrix for variables considered in multiple linear regression analysis to examine linkages between hydrologic flow conditions, erosion, and accretion.