Mapping spatial patterns of stream power and channel change along a gravel-bed river in northern Yellowstone

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A B S T R A C T

Stream power represents the rate of energy expenditure along a river and can be calculated using topographic data acquired via remote sensing or field surveys. This study sought to quantitatively relate temporal changes in the form of Soda Butte Creek, a gravel-bed river in northeastern Yellowstone National Park, to stream power gradients along an 8-km reach. Aerial photographs from 1994 to 2012 and ground-based surveys were used to develop a locational probability map and morphologic sediment budget to assess lateral channel mobility and changes in net sediment flux. A drainage area-to-discharge relationship and DEM developed from LiDAR data were used to obtain the discharge and slope values needed to calculate stream power. Local and lagged relationships between mean stream power gradient at median peak discharge and volumes of erosion, deposition, and net sediment flux were quantified via spatial cross-correlation analyses. Similarly, autocorrelations of locational probabilities and sediment fluxes were used to examine spatial patterns of sediment sources and sinks. Energy expended above critical stream power was calculated for each time period to relate the magnitude and duration of peak flows to the total volumetric change in each time increment. Collectively, we refer to these methods as the stream power gradient (SPG) framework. The results of this study were compromised by methodological limitations of the SPG framework and revealed some complications likely to arise when applying this framework to small, wandering, gravel-bed rivers. Correlations between stream power gradients and sediment flux were generally weak, highlighting the inability of relatively simple statistical approaches to link sub-budget cell-scale sediment dynamics to larger-scale driving forces such as stream power gradients. Improving the moderate spatial resolution techniques used in this study and acquiring very-high resolution data from recently developed methods in fluvial remote sensing could help improve understanding of the spatial organization of stream power, sediment transport, and channel change in dynamic natural rivers.

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1. Introduction

Rivers exhibit tremendous variability across space and time because of variations in streamflow and sediment input. Spatial variation in flow strength drives erosion and deposition, but local geomorphic context and disturbance history also play important roles (Lecce, 1997; Fonstad, 2003; Thompson and Croke, 2013). Many uncertainties persist regarding these form–process interactions owing to the failure of conceptual frameworks such as downstream hydraulic geometry to adequately predict the complex flow and sediment transport seen across a range of scales in natural rivers (Fonstad and Marcus, 2010). This problem is further complicated by the challenge of obtaining high-resolution data at broad basin scales over timescales relevant to channel adjustment. Methods beyond traditional locally intensive field surveys are needed to quantitatively characterize the heterogeneous nature of rivers, and remote sensing has shown considerable potential for providing continuous, high-resolution, spatial data at watershed extents (Marcus and Fonstad, 2008). This study analyzes the spatial organization of stream power and morphologic change from aerial photography, LiDAR, and field surveys to quantify relationships among the driving forces of flow and sediment response in a dynamic gravel-bed river.

Measurement of morphologic change from aerial photography is a long established way to characterize long-term patterns and rates of planform change and to estimate volumes of scour and fill associated with these alterations in channel morphology (Ham and Church, 2000; Lane et al., 2003; Zanoni et al., 2008). Graf (1981, 1984, 2000) introduced locational probability maps as an efficient means of quantifying historical channel dynamics, and more recent studies have applied the method to a variety of river channel environments (Wasklewicz et al., 2004; Ham and Church, 2012). Changes in channel location summarized by a locational probability map also can be used to construct a sediment budget by measuring the spatial extent of erosion and deposition (Gaeuman et al., 2003). Advantages of this ‘morphologic approach’ include insights into sediment transfer over time, exposing variations in transport and storage along the channel, and providing information on
rates of bank erosion, channel widening, and changes in channel planform (Ashmore and Church, 1998; Ham and Church, 2000). Both the locational probability map and morphologic sediment budget were used in this study to quantify lateral channel change between 1994 and 2012 for a stream in northeast Yellowstone National Park.

These measured changes in channel morphology and sediment transport are related to stream power, the rate of energy expenditure per unit distance along a river (Bagnold, 1966). Stream power depends on the rate at which potential energy is converted to kinetic energy as water travels downstream, which in turn is determined by discharge and slope. Power per unit length of stream is referred to as cross-sectional stream power ($\Omega$) and is calculated as

$$\Omega = \rho g Q S_w$$

(1)

where $\rho$ is the density of water, $g$ is the gravitational acceleration constant, $Q$ is discharge, and $S_w$ is the water surface slope, which is used to estimate the energy gradient. Dividing cross-sectional stream power by the width of the cross section provides energy expenditure per unit bed area of the channel, or mean stream power ($\omega$), and is defined as

$$\omega = \frac{\Omega}{w}$$

(2)

where $w$ is channel width. For consistency, all terminology relating to stream power calculation follows Rhoads (1987). Cross-sectional stream power has been used as a predictor of channel dimensions and pattern (Graf, 1983; Lecce, 1997) and for channel mobility thresholds (Bull, 1979; Magilligan, 1992), whereas mean stream power provides information on channel dynamics and has been related to bed sediment entrainment and bedload transport rate (Ferguson, 2005; Petit et al., 2005; Parker et al., 2011). Both $\Omega$ and $\omega$ have been used to qualitatively assess the spatial distribution of channel change (Vocal Ferencevic and Ashmore, 2012; Biron et al., 2013; Bizzi and Lerner, 2013). In this study, we related mean stream power to channel morphodynamics because this quantity accounts for variations in channel width and is associated with entrainment, transport rate, and channel stability.

While $\omega$ determines sediment transport capacity, along-stream changes in $\omega$ determine whether and to what extent erosion or deposition will occur. Along-channel changes in $\omega$ can be calculated by converting Cartesian coordinates to a channel-fitted coordinate system, with a streamwise axis $s$ following the channel centerline and a second axis $n$ normal to the centerline (Legleiter and Kyriakidis, 2006). Mean stream power gradient ($\partial \omega / \partial s$), or the rate of change in $\omega$ per unit distance downstream, should indicate areas where energy expenditure occurs more or less rapidly and consequently where transport capacity increases or decreases, respectively. Bizzi and Lerner (2013) found unique combinations of $\Omega$ and $\omega$ gradients matched specific channel features classified using the River Habitat Survey, but to our knowledge the influence of such stream power gradients on sediment transport has not been quantified. The conceptual illustration in Fig. 1 illustrates theoretical sediment response to $\partial \omega / \partial s$. Greater deposition is expected to occur where stream power declines more rapidly downstream as shown on the left side of the figure, but deposition is projected to decrease as mean stream power gradient approaches 0. Conversely, the largest amounts of erosion are expected to occur where the greatest downstream increases in stream power occur. Net flux is anticipated to change from net depositional where $\partial \omega / \partial s$ is negative to erosional where $\partial \omega / \partial s$ is positive. This model assumes $\omega$ exceeds a critical mean stream power ($\omega_c$) at either the upstream point, downstream point, or at both locations because movement of bed material load is negligible when $\omega < \omega_c$.

In natural rivers, the application of this simple conceptual framework is complicated by variations in the magnitude, frequency, and duration with which $\omega$ exceeds $\omega_c$ because of spatial and temporal differences in discharge, slope, and grain size (Wolman and Miller, 1960; Costa and O’Connor, 1995). To enable comparison among time periods, the amount of energy expended above $\omega_c$ between two points in time, referred to here as excess energy per unit bed area ($\epsilon$), can be calculated and used as a metric of sediment transport capacity. Because larger $\epsilon$ is expected to entrain and deposit more sediment, greater energy expenditure should lead to a larger amount of geomorphic work and total sediment flux ($T$), defined as the sum of gross erosion ($E$) and gross deposition ($D$).

The objective of this study was to assess the spatial distribution of channel change and determine if the observed changes could be quantitatively related to the driving forces of Soda Butte Creek. This was tested by examining the three following hypotheses:

1. Areas that experience greater channel change coincide with larger positive and negative values of $\partial \omega / \partial s$.
2. Reaches over which $\omega$ increases significantly and exceeds $\omega_c$ experience net erosion and act as sources of sediment to downstream reaches, whereas reaches over which $\omega$ decreases significantly and drops below $\omega_c$ experience net deposition and act as sinks for material eroded from upstream reaches.
3. Locations where $\omega$ exceeds $\omega_c$ with the greatest frequency and magnitude will have the highest values of $\epsilon$ and will correlate with the largest $T$ values, while locations where $\omega$ rarely, if ever, surpasses $\omega_c$ will have the lowest $\epsilon$ and $T$ values.

2. Study area and methods

These hypotheses were examined in the context of the study area by using aerial photographs from 1994 to 2012 and cross section surveys acquired in 2007 to develop a locational probability map and morphologic sediment budget to assess lateral channel mobility and sediment fluxes. Stream power was calculated using discharge acquired from a discharge-to-drainage area relationship for gages in the greater Yellowstone region and slope determined from a digital elevation model (DEM) developed from light detection and ranging (LiDAR) data. Local and lagged relationships between stream power and volumes of erosion, deposition, and net sediment flux were related using cross-correlation, while values of locational probability and sediment fluxes were correlated to their own lagged spatial series via autocorrelation. Energy expended above critical stream power was also calculated for each time period to compare magnitude and duration of peak flows...
to total volume change in each time increment. Together, we refer to these methods collectively as the stream power gradient (SPG) framework. Notation was used for clarity and brevity throughout this study, and a full list is provided in the notation section.

2.1. Study area

2.1.1. Drainage basin characteristics

Soda Butte Creek drains a 256-km² glaciated watershed in the north-eastern corner of Yellowstone National Park, USA (Fig. 2). This wandering gravel-bed river features diverse channel planforms and traverses a variety of valley floor environments (Legleiter, 2012). Channel patterns include: meandering, single-thread channels in the lowest-gradient reaches; braided channels with active gravel bars commonly found below valley constrictions; straight channels where the stream is confined by bedrock, alluvial fans, or landslide accumulations; and anastomosing channels divided by relatively stable grassy islands (Meyer, 2001). This study focuses on an ~8-km reach of Soda Butte Creek that encompasses all of these planforms and extends downstream from the Trout Lake landslide to Soda Butte’s confluence with the Lamar River (Fig. 2).

The following description of the Soda Butte Creek watershed is based upon earlier work by Meyer (1995, 2001). The drainage basin of Soda Butte Creek ranges from 2000 m at the confluence with the Lamar River up to 3365 m at Amphitheater Peak. Average annual precipitation is strongly orographic, increasing from 360 mm at the Lamar River confluence to 660 mm at Cooke City, MT (2302 m), and as much as 1300 mm at elevations over 3000 m along the eastern park boundary. Vegetation distributions follow this strong climatic gradient, as the dry grasslands and sagebrush (Artemisia tridentata) steppe that predominate in the lower Soda Butte valley transition to Douglas fir (Pseudotsuga menziesii) and mixed-conifer stands dominated by lodgepole pine (Pinus contorta) at higher elevations. Wet meadows consisting of grasses and sedges also occur along lowermost Soda Butte Creek near the Lamar River confluence, and small mesic meadows are scattered across lower alluvial fans, moraines, and ridges. Most of the annual precipitation falls as winter snow and comprises the majority of the annual runoff, with the greatest potential for geomorphic work occurring during the snowmelt period in May and June. Localized, short-lived, convective summer storms add only a small fraction to the total annual runoff but may produce significant discharges in steep tributary drainages that can act as an important source of sediment and create short periods of intense geomorphic work.

Discharge measurements were recorded at a U.S. Geological Survey (USGS) stream gage beginning on 1 October 1988 at a footbridge spanning Soda Butte Creek ~3 km above its confluence with the Lamar River. Although this gage was deactivated on 30 September 2008, the Lamar River gage indicated in Fig. 2 has monitored discharge since 1923 and includes daily records for the 1994–2012 study period. Discharges on Soda Butte Creek for the period after the gage was decommissioned were predicted using a drainage area-to-discharge relationship of the form

\[ Q_{SBC} = \frac{Q_{Lamar}}{DA_{Lamar}} \times DA_{SBC} \]  

(3)
where \( Q_{\text{SBC}} \) is the predicted daily discharge in \( \text{m}^3 \text{s}^{-1} \), \( Q_{\text{Lamar}} \) is the recorded daily discharge at the gage near Tower, and \( \Delta A_{\text{Lamar}} \) and \( \Delta A_{\text{SBC}} \) are the drainage areas at each gage site. The mean difference between observed \( Q_{\text{SBC}} \) and predicted \( Q_{\text{SBC}} \) when data for both gages were available was \(-0.02 \pm 3.15 \text{ m}^3 \text{s}^{-1} \) (residual + standard deviation). Annual peak discharges for Soda Butte Creek between 2009 and 2012 were estimated using this relationship and are shown in Fig. 3 along with peak discharges recorded at the Soda Butte Creek gage between 1994 and 2008 and at the Lamar River gage over the entire study period.

### 2.2.2. Geologic and geomorphic context

The Soda Butte Creek watershed encompasses a heterogeneous mixture of lithologies and has been extensively glaciated. Higher elevations are largely composed of Eocene andesitic volcanic rocks that experienced regional uplift in the late Neogene followed by extensive erosion during the Pinedale glaciation (Meyer, 1995). These processes resulted in steep slopes of exposed, easily erodible bedrock conducive to the formation of debris avalanches, landslides, and alluvial fans. Lower elevations are a mixture of volcanic rocks eroded from the higher elevations and Paleozoic carbonates and shales. Steep slopes of erodible bedrock and heavy snows at high elevations create the potential for significant channel change by delivering abundant coarse sediment and generating large floods. While the largest recorded flood on Soda Butte Creek (69 m^3 s^{-1}) occurred in 1996 because of rapid runoff generation from rain-on-snow events and warm late spring temperatures, tree-ring dating indicates that even larger floods occurred in 1918 and ca. 1873 (Meyer, 2001). Estimated peak discharges from 1918 and ca. 1873 are 2 to 3 times larger than the 1996 peak discharges for Soda Butte Creek between 2009 and 2012. The two largest floodplain from freemining features (Hughes et al., 2006). Georeferencing root-mean-square error ranged from 0.52 to 1.33 m (Table 1). All images were transformed using a second-order polynomial warp and nearest neighbor resampling.

Polygons outlining the wetted channel were produced for each year in the time series by using a spectral band threshold implemented in MATLAB. A near-infrared (NIR) band was preferred for this process because strong absorption of this wavelength by water created a clear contrast with brighter terrestrial features. We used a red band for the 2006 image because no NIR band was available for this year. A wetted channel polygon was manually digitized from the 1994 panchromatic image because brightness differences between water and terrestrial features were subtle and inconsistent. Polygons generated by the spectral band threshold required minor manual editing to remove isolated shadow pixels or correct pixels affected by sun glint. The edited channel polygons for each year were converted into binary rasters and weighted based on the time period between each successive image in the time series. Following Graf (2000), weights were calculated as

\[ W_n = t_n / m \]

where \( W_n \) is the weight assigned to each time period, \( t_n \) is the number of years elapsed since the previous image in the time series, and \( m \) is the total length of record. For example, \( t_{2001} = 7 \) years because the previous image in the time series was aerial photography from 1994, seven years prior to the 2001 image. The final locational probability map weighted and combined the raster channel masks using the expression

\[ p = (W_{1994} F_{1994} + W_{2001} F_{2001} + \ldots + W_{2012} F_{2012}) \]

where \( p \) is the percentage of time each pixel was occupied by the channel in the 1994–2012 time period, and \( F_n \) is the channel occurrence in year \( n \), equal to 1 for occurrence or 0 for absence.

### 2.2.2. Morphologic sediment budget

Areas of erosion and deposition were quantified by using a Random Forest classification to develop land cover change maps (Gislason et al., 2006). Four classes (water, gravel, vegetated, or shadow) were identified on a per-pixel basis and then inspected and manually edited to improve accuracy. The 1994 land cover map was digitized and classified manually because of a lack of spectral bands to drive the classification algorithm. Each pair of successive images was compared to identify class transitions. The resulting land cover change maps were used to

![Fig. 3. Annual peak discharge at the Lamar River and Soda Butte Creek gage locations highlighted in Fig. 2. The horizontal line represents the median peak discharge (251 m^3 s^{-1}) at the Lamar gage based on 73 years of record.](image-url)
determine areas of erosion and deposition within a series of 220 budget cells with a lateral extent defined by the union of the bankfull channel polygons for the two time periods and a downstream length equal to 30 m. Volumes of erosion and deposition were obtained by multiplying these areas by a representative bank or bar height determined from 20 channel cross sections surveyed in the field in 2007. These volumes were calculated based on three representative heights representing depths of scour and fill (Table 2). Bank height measurements were split into two groups based on a difference in vegetation cover midway through the 8-km study reach. While the upper 5 km of the study area contains ‘dry meadow’ (cf., Micheli and Kirchner, 2002), sage-dominated bank cover, the remaining 3 km transitions to more cohesive, higher vertical banks with ‘wet meadow’ grasses and sedges (Fig. 4). The transition from sage-dominated banks to wet meadow banks occurs near a footbridge across Soda Butte Creek that served as the dividing line between the two bank height distributions. Gravel bars measured throughout the entire 8-km study reach comprised the third group of heights. Net sediment fluxes (ΔV) were calculated for each budget cell and for the entire 8-km study area by summing E and ΔV values.

A correction applied to each time interval helped reduce the false appearance of erosion caused by higher water levels on the latter date of successive images (or deposition with lower discharge on the later date). Net sediment flux was adjusted to account for variations in discharge between each image by using the reach-averaged, at-a-station hydraulic geometry relation w = αQ^β to determine the change in wetted channel width for each budget cell per unit change in discharge (Ham and Church, 2000). Vegetated islands were converted to the gravel land cover class to ensure that their erosion was multiplied by the more realistic gravel bar height than by the vegetated bank height. The edited land cover maps produced from these corrections were used to calculate E, D, and ΔV.

### 2.2.3. Stream power maps

The discharges used to calculate stream power along Soda Butte Creek were estimated with a power law equation developed from a drainage area-to-discharge relationship between 15 gages in the greater Yellowstone region. As in previous studies examining the spatial distribution of stream power in a watershed (Knighton, 1999; Jain et al., 2006; Vocal Ferencevic and Ashmore, 2012; Biron et al., 2013), this relation took the form

\[ Q = \alpha A^\beta \]

where Q is discharge in m³ s⁻¹, A is drainage area in km², and α and β are calculated coefficients. The median annual peak discharge (Qₘᵦₑₜ) was used as a representative relatively frequent, geomorphically effective flow (Barker et al., 2009; Bizzi and Lerner, 2013). Cumulative drainage area along Soda Butte Creek were calculated using ArcGIS hydrology tools with a National Elevation Dataset 1/3 arc sec DEM. We predicted discharge as a function of drainage area along the channel derived from a flow accumulation grid via Eq. (5).

A representative slope value for each budget cell was determined using a 1-m² LiDAR DEM acquired in 2007 by the National Center for Airborne Laser Mapping. The DEM was initially smoothed using a 5 × 5 median filter and then resampled into 5-m pixels by aggregating based on the minimum value (Biron et al., 2013). A median filter was used to avoid anomalous DEM values based on LiDAR returns from within the wetted channel. Although most NIR laser pulses are absorbed by the water column, any pulses that do return to the sensor travel slower in water than in air and thus will yield much lower elevations than surrounding pixels. A median filter eliminates these anomalously low values, and resampling based on the minimum value ensures water surface elevations are selected over bank or gravel bar elevations when aggregated. Slope values were calculated from the resulting DEM by extracting elevation values along the channel centerline and dividing the elevation difference of sequential points by the distance between them. The representative slope value assigned to each budget cell was calculated by averaging slope values between 60 m upstream to 60 m downstream from each budget cell centroid, a distance corresponding to two budget cells upstream and two budget cells downstream.

Mean stream power at Qₘᵦₑₜ was calculated using Eq. (2). Width for each budget cell was acquired from the bankfull channel polygons for the four time intervals. Mean stream power gradient (∂Q/∂s) was calculated by subtracting ω in budget cell i from ω in cell i − 1 and dividing the difference by the distance between the centroid of each budget cell along the channel centerline (Fig. 5A). In this way positive ∂Q/∂s values indicate downstream increases in ω, while a negative ∂Q/∂s indicates that ω is decreasing from one budget cell to the next. Parentheses are

![Fig. 4. Banks above the footbridge (A) have noncohesive gravels and are dominated by dry xeric shrub and sagebrush, while banks below the footbridge (B) have finer-grained cohesive banks dominated by wet riparian grasses.](image-url)
used throughout the rest of the text to denote location (e.g., \( \omega \) at budget cell \( i \) would be denoted as \( \omega(i) \)).

The amount of energy expended beyond critical mean stream power (\( \omega_c \)) in each budget cell was calculated in addition to \( \partial \omega / \partial s \) to understand the spatial distribution of energy available for sediment transport and to account for differences in the magnitude and frequency of discharge during the time interval between successive images. Excess energy per unit bed area (\( \varepsilon \)) expended over \( \omega_c \) for each time period was determined by calculating \( \omega_c \) for each date in the four time intervals from mean daily discharge (\( Q_d \)) and comparing the values to \( \omega_c \) calculated using Eqs. (10) and (16) from Parker et al. (2011), which relate \( \omega_c \) to slope and grain size. Variations in slope drove differences in \( \omega_c \) between budget cells because a constant median grain size of 29 mm (acquired from Wolman pebble counts throughout the study area) was used for all budget cells. If \( \omega \) calculated from \( Q_s \) exceeded \( \omega_c \), the difference between \( \omega \) and \( \omega_c \) was multiplied by the number of seconds in a day to obtain \( \varepsilon \) in joules. The cumulative excess energy per unit bed area (\( \varepsilon_c \)) values for each budget cell in the four time periods were divided by the number of days \( \omega \) exceeded \( \omega_c \) to obtain the average excess energy expenditure per unit bed area (\( \varepsilon_w \)) across each time period. Average excess energy per unit bed area was then related to \( \DeltaV \) and total flux (\( T \)). Using \( \varepsilon_w \) rather than \( \varepsilon_c \) served to account for the different number of days in each time interval.

### 2.2.4. Autocorrelation and cross-correlation

The spatial variation of lateral channel mobility and sediment movement along Soda Butte Creek was quantified using autocorrelation, with the goal of understanding spatial patterns of channel change throughout the study period. Autocorrelation functions (also known as correlograms) quantify the similarity between observations of the same variable based on the lag distance between them; similar methods are widely used in time series analysis (Davis, 2002). This statistical technique has been used to examine the variability of width and depth in Soda Butte Creek (Fonstad and Marcus, 2010) and to estimate grain size based on image texture (Carbonneau et al., 2004). Autocorrelation was calculated for \( E, D, \DeltaV \), and average locational probability (\( <P> \)), which was determined by averaging all pixel values where \( P > 0 \) in each budget cell. Autocorrelation is similar to the example shown in Fig. 5, except that \( <P> \) and sediment fluxes at cell \( i \) were compared to the same variable at cell \( i + j \) rather than a different variable at the latter location.

Relating one variable to a second, spatially lagged variable is known as cross-correlation, and we used this method to relate \( \partial \omega / \partial s \) to downstream values of \( E, D, \) and \( \DeltaV \). The goal of this analysis was to assess the spatial relationship between changes in stream power and transfers of sediment. Assuming that only budget cells with \( \omega \) greater than \( \omega_c \) were capable of moving sediment at \( Q_{MED} \), cells with \( \partial \omega / \partial s \) meeting one of the four conditions listed in Table 3 were selected for correlation with downstream sediment fluxes. Consecutive budget cells where \( \omega \) was lower than \( \omega_c \) were excluded from the analysis because of negligible sediment movement in these cells.

Mean stream power gradient for the budget cells meeting the criteria in Table 3 were compared to \( E, D, \) and \( \DeltaV \) values at cells \( i \) through \( i + 10 \) downstream by calculating cross-correlation between \( \partial \omega / \partial s(i) \) and sediment flux at cell \( i + j \) (Fig. 5B). The resulting correlation coefficients were then plotted against the lag distance to examine the relationship between \( \partial \omega / \partial s \) and downstream sediment fluxes.

Hypotheses (1) and (2) were tested by using autocorrelation and cross-correlation to compare \( \partial \omega / \partial s(i) \) to \( E, D, \) and \( \DeltaV(i + 1) \). Assuming \( \partial \omega / \partial s \) leads to the strongest expression of sediment change in the nearest cell downstream from it, scatterplots were also used to assess hypothesis (2) by relating \( \partial \omega / \partial s(i) \) to \( E, D, \) and \( \DeltaV(i + 1) \). Similarly, \( \varepsilon_w(i) \) was plotted against \( \DeltaV(i + 1) \) and \( T(i + 1) \) to examine hypothesis (3) that greater \( \varepsilon_w \) correlates with larger total flux.

### 3. Results

#### 3.1. Locational probability map

Fig. 6A and B illustrates the locational probability map of Soda Butte Creek in the context of the valley topography. Zones of high and low probabilities alternate along the 8-km stretch, with values ranging from 0.05 in highly dynamic reaches to 1 where the channel has remained stationary. Fig. 6A summarizes the variation in budget cell-averaged locational probability along Soda Butte Creek.

Laterally stable zones of high locational probability occur where various lateral confinements restrict channel movement. For example, the uppermost portion of the study area (Fig. 6A, square) saw limited...
channel movement during the study period owing to confinement by the Trout Lake landslide and alluvial terraces to the northwest and alluvial fan deposits to the southeast. The three largest floods recorded at the Soda Butte Creek gage (1995, 1996, 1997) produced noticeable erosion of cutbanks along the first two bends in this area; but the channel migrated little during the study period, remaining close to its present location throughout. Soda Butte Creek also remained immobile throughout the study period near the footbridge and stream gage (Fig. 6B, circle) where bedrock outcrops at the surface. Downstream from this point to the confluence with the Lamar River, active channel width remained limited because of the cohesive wet meadow banks, the Foster Lake landslide deposits to the north, terraces to the south, and a large, stable island near the confluence. Although the 1995–1997 floods increased active channel width between the 1994 and 2001 images, a t-test comparing active channel widths above and below the footbridge indicated that widths were significantly greater in the dry meadow upstream reach than where more cohesive banks are colonized by wet meadow vegetation ($P < 0.001$). A second t-test revealed that the difference in active channel width between the reaches did not correspond to significantly different locational probability values ($P = 0.23$).

Zones of higher lateral mobility were expressed as of lower locational probability values and occurred in unconfined, alluvial reaches where channel movement was not restricted by strong lateral controls. The triangle in Fig. 6A highlights a wide, braided reach where Soda Butte Creek

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**Table 3**
The four cases required for comparison of $\partial \omega / \partial s$ to $E$, $D$, and $\Delta V$ and the hypothesized sediment response in budget cell $i$ or downstream budget cells $i + j$; the symbols are used in Figs. 11 and 12 to relate $\partial \omega / \partial s(i)$ and $\omega(i)$ to $E(i + 1)$, $D(i + 1)$, $\Delta V(i + 1)$, and $T(i + 1)$.

<table>
<thead>
<tr>
<th>Case</th>
<th>Description</th>
<th>Hypothesized implication</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>1:</td>
<td>$\omega(i) &gt; \omega(i - 1) &gt; \omega_c$</td>
<td>$\omega$ increases downstream and is above $\omega_c$ for both budget cells</td>
<td>Erosion</td>
</tr>
<tr>
<td>2:</td>
<td>$\omega(i) &gt; \omega_c &gt; \omega(i - 1)$</td>
<td>$\omega$ increases downstream and exceeds $\omega_c$ in cell $i$</td>
<td>Minor erosion</td>
</tr>
<tr>
<td>3:</td>
<td>$\omega(i - 1) &gt; \omega(i) &gt; \omega_c$</td>
<td>$\omega$ decreases downstream but is above $\omega_c$ for both budget cells</td>
<td>Minor deposition</td>
</tr>
<tr>
<td>4:</td>
<td>$\omega(i - 1) &gt; \omega_c &gt; \omega(i)$</td>
<td>$\omega$ decreases downstream and falls below $\omega_c$ in cell $i$</td>
<td>Deposition</td>
</tr>
</tbody>
</table>

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**Fig. 6.** Locational probability maps for the upstream (A) and downstream (B) segments of Soda Butte Creek study area. Symbols are discussed in the text. (C) Plot of average locational probability by budget cell along the study area. Downstream distance is plotted using kilometers rather than number of budget cells to provide a more easily understandable unit of measurement.
shifted laterally between each pair of images to produce zones of low probability and islands of zero probability distributed across a broad valley floor. This area was dynamic even during some of the lowest discharges on record; between 2006 and 2009 this reach experienced significant lateral change, whereas the majority of the 8-km study area remained stable.

3.2. Morphologic sediment budget

Table 4 lists $E, D,$ and $ΔV$ values for the entire study area in each time interval. For all four time periods erosion exceeded deposition, resulting in a negative net sediment flux. Net sediment flux volumes for each budget cell were divided by budget cell area to help conceptualize the height of scour and fill for each time interval and are displayed in Fig. 7. These normalized values change for each budget cell between the four time intervals, but erosion was generally greater downstream of the footbridge than in the more laterally dynamic segments of Soda Butte Creek farther upstream.

3.3. Stream power maps

Maps of $ω$ at $Q_{100}$ for the four time intervals were generated by applying Eq. (2) to each budget cell (Fig. 8). The maps exhibit a heterogeneous patchwork of $ω$ values, ranging from 2 to 125 W m$^{-2}$. Values of $ω$ are primarily driven by changes in width: larger values occurred in narrow parts of the channel and smaller values in the widest budget cells. However, budget cells with similar widths in different reaches of the study area show a range of $ω$ values, indicating $ω$ was also influenced by local slope. Changes in $Q$ played the least important role in the variation of $ω$ because no major tributaries joined Soda Butte Creek in this area, and thus increases in $Q$ from the upper end of the study area to the Lamar River confluence were slight and gradual.

3.4. Spatial structure of locational probability and sediment flux

Autocorrelation plots for $E, D,$ $ΔV,$ and $<P>$ in each time interval are displayed in Fig. 9. The correlation coefficients for $E, D,$ and $ΔV$ all had a similar trend, decreasing steadily until the correlation was no longer statistically significant around 4–7 budget cells downstream. The autocorrelation for $<P>$ does not decrease as rapidly as $E, D,$ and $ΔV$ and remains statistically significant for 8 budget cells downstream.

3.5. Spatial structure of stream power gradients and sediment fluxes

Cross-correlation plots relating lags of $E, D,$ and $ΔV$ to $Δω/Δs$ are presented in Fig. 10. This analysis indicated a lack of consistent, significant correlation between $E, D,$ or $ΔV$ and $Δω/Δs$ at any lag distance between 0 and 10 budget cells. A few isolated lags in each of the cross-correlation plots were marginally significant, but these results were not consistent across the four time intervals. Further, the greatest correlation coefficient was only $−0.25$; these weak correlations suggest that $Δω/Δs$ was not strongly related to $E, D,$ or $ΔV$ in a direct, linear manner detectable by this relatively simple statistical analysis.

Values of $Δω/Δs(i)$ were related to $E(i + 1), D(i + 1),$ and $ΔV(i + 1)$ for each time interval in Fig. 11. The largest values of $E$ and $D$ occurred where $Δω/Δs$ approaches zero, and both gradually decreased with larger positive and negative $Δω/Δs$ values. These results contradicted hypothesis (1) and sediment fluxes predicted by Fig. 1. Mean thickness of scour often exceeded that of fill, which lead to mostly net erosive $ΔV$ values. The lack of a strong and consistent relationship between negative $Δω/Δs$ values and net deposition differed from hypothesis (2). ANOVA and Tukey range tests contrasted with the hypothesized implications from Table 3 because there were no significant and consistent differences between the means of the four cases for $E, D,$ and $ΔV$ (Table 5).

Plots relating $ε_{c}(i)$ to $ΔV(i + 1)$ and $T(i + 1)$ are shown in Fig. 12. Values of $ΔV$ have the largest range between $ε_{c}$ values of 0 and 1.5 MJ, above which higher $ε_{c}$ values converge toward a $ΔV$ of 0 m$^3$. The $ΔV$ values from 1994 to 2001 have a steady range between $ε_{c}$ values of 0 and 2 MJ, but converge toward 0 m$^3$ similar to the other time intervals where $ε_{c}$ exceeds 2 MJ. Total flux values follow a similar pattern as $ΔV$, with the highest range of $T$ values occurring between $ε_{c}$ values of 0 and 2 MJ. All four time intervals decrease toward $T = 0$, where $ε_{c}$ values surpass the peak $T$ values, contradicting hypothesis (3) that higher amounts of $ε_{c}$ lead to higher volumes of $E$ and $D$.

4. Discussion

4.1. Locational probability map for quantifying lateral channel mobility

The locational probability map highlights how active channel width reflects the degree of channel confinement. Soda Butte Creek below the
footbridge had a narrower active channel than the broad valley floor upstream, but this did not lead to a statistical difference in average locational probability between the reaches. The observation of a wider active channel in dry meadow reaches with xeric vegetation compared to the more cohesive wet meadow reaches supports past findings of greater bank erodibility in dry meadow over wet meadow areas (Micheli and Kirchner, 2002). Areas of high locational probability caused by outcropping bedrock, geomorphic features, and stable islands, as well as areas of low locational probability owing to a lack of lateral controls, were also reported by Graf (2000) and Wasklewicz et al. (2004). The occurrence of high and low probability areas dictated by geomorphic features indicates that streams of varying sizes in a range of climates all feature zones of greater and lesser lateral mobility associated with similar geomorphic contexts.

**Fig. 9.** Autocorrelations for E, D, and $\Delta V$. Lines examining the same change type were plotted together to identify any strong correlations and/or consistent trends between E, D, or $\Delta V$ at cell $i$ and E, D, or $\Delta V$ at cell $i + j$. The autocorrelation for average locational probability is plotted on all three graphs for comparison. Dotted horizontal lines indicate statistical significance.

**Fig. 10.** Cross-correlations comparing $\partial \omega / \partial s$ at cell $i$ to E, D, and $\Delta V$ at cell $i + j$. Dotted horizontal lines indicate statistical significance.
Unlike Graf (2000), some of the data sets we used to produce the locational probability map were not acquired at low-flow conditions. The wetted channel was used to produce the mask for each time period, but because 2001 and 2009 were collected at a higher discharge than the other three images they exaggerate the extent of the low-flow channel (Table 1). Locational probability of some floodplain locations were also likely underestimated because of the large time intervals between each set of images. Graf (2000) noted the importance of having images that highlight geomorphically significant events rather than every year, but the shifts in channel position that occurred between 2006 and 2009 in the braided reach of Soda Butte Creek highlighted how significant changes can occur even during a period of relatively low peak flows. These results implied that high temporal resolution repeat imagery is highly desirable, if not necessary, for calculating locational probabilities in a dynamic river.

4.2. Caveats and sources of uncertainty in morphologic sediment budgeting

A lack of annual images also can be an important source of uncertainty in morphologic sediment budgeting because compensating scour and fill during the time interval between images cannot be detected. Along with the inability to detect wash load transmitted through the study reach without any morphologic expression, this general limitation implies that the estimated $E$, $D$, and $\Delta V$ represent only lower bound estimates of the true sediment fluxes. In this study, another potential shortcoming of the morphologic approach was the assumption that sampled bank and bar heights acquired in 2007 remained unchanged between 1994 and 2012 and were representative of the larger reaches for which they were used to estimate volumes of erosion and deposition. Our analysis also assumed the bank heights were independent and identically distributed, but a more rigorous approach might have considered the spatial correlation of bank heights with volumes of change.

In addition to the fundamental limitations inherent to the morphologic approach, several other sources of uncertainty must be acknowledged as well. For example, pixels classified as shadow were discarded and introduced some uncertainty because geomorphic changes could not be inferred unambiguously in shadowed areas. Pixels classified as shadow ranged between 0.5 and 1% for each image in the time series, and the maximum number of pixels in any one budget cell was about 200. While this indicates it is possible 200–500 m$^2$ of sediment could

Table 5
ANOVA and Tukey range test $P$-values to determine if means among the four cases highlighted in Table 3 are significantly different for each time interval (asterisks indicate significant difference between case means at the $P < 0.05$ level).

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<td>0.17</td>
<td>0.02*</td>
<td>0.02*</td>
<td>0.05*</td>
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<td>0.87</td>
<td>0.75</td>
<td>0.94</td>
<td>0.22</td>
<td>0.33</td>
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</tr>
<tr>
<td>1 vs. 3</td>
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<td>0.96</td>
<td>0.25</td>
<td>0.11*</td>
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</tr>
<tr>
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<tr>
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<tr>
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<td>3 vs. 4</td>
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Fig. 11. Plots of $\partial \omega / \partial s$ versus $E(i + 1), D(i + 1)$, and $\Delta V(i + 1)$ for the four time intervals. These are the same as the lag 1 $(y(i + 1))$ scatterplot embedded in the cross-correlograms shown in Fig. 5. Each symbol represents one of the four conditions described in Table 3.
have gone undetected in cells with the most shadow coverage, the actual amount was likely less and most budget cells had few if any shadow pixels. Still, sediment volumes in budget cells with shadows were only lower bounds because undetected erosion or deposition might have occurred in areas obscured by shadows. Misclassified land cover and mixed pixels that contained some combination of the four land cover classes were another source of uncertainty. However, the land cover maps were manually edited to address these problems, and any lingering classification errors were considered negligible. Additional uncertainty might have entered into the sediment budget calculations owing to highly disparate discharges among the images (Table 1) that might not have been fully accounted for by the width–discharge correction (Ham and Church, 2000).

4.3. Further limitations of the morphologic sediment budget employed in this study

In this study all four time intervals we considered experienced net erosion. Ham and Church (2000) also found all four of their study intervals to be net erosive and attributed these results to limited sediment supply in the Chilliwack River. While a lack of sediment to Soda Butte Creek seems unlikely because of erodible valley walls, these valley walls are not directly coupled to the river. Soda Butte Creek thus could be supply-limited to some extent if sediment produced on hillslopes is stalled by ‘buffers’ and not transferred efficiently to the channel (Fryirs, 2013). However, a more plausible explanation for the net erosive fluxes is that calculated volumes of erosion and deposition were biased toward erosion owing to greater erosion heights (i.e., vegetated bank to water) than deposition heights (i.e., water to gravel bar; Table 2). Land cover changes from water to gravel or water to vegetation both were multiplied by the bar height because deposition occurred in the active channel where gravel bars were located. Gravel bars are slowly accreted into the floodplain and built to the height of the floodplain over timescales much longer than examined by this study. The change from water to vegetation usually occurs where gravel is deposited in the active channel and seasonal vegetation grows on the bar; thus these areas of deposition were multiplied by the bar height. Processes such as floodplain shaving led to the difference between heights of scour and fill and, in turn, an uneven balance in sediment budgets because multiple pixels of deposition would be needed to equal one pixel of bank erosion (Lauer and Parker, 2008). The sediment budget is further biased toward erosion because bank erosion likely contains some fine sediment that will be removed from the study area as suspended load and not expressed as deposition within the study reach. These imposed imbalances between erosion and deposition were another limitation of the morphologic sediment budget as implemented in this study. Our results suggest that high spatial resolution data such as repeat LiDAR surveys are required to more accurately characterize channel change (Croke et al., 2013).

While the morphological sediment budget described here only accounted for volumes of erosion and deposition between each time interval, developing a sediment routing model could help quantify rates of bed material transfer and storage. For example, Gaeuman et al. (2003) developed a morphologic sediment budget on the Duchesne River by distributing eroded gravel downstream according to a probability distribution of particle path lengths parameterized by the mean travel distance. A similar approach could be implemented on Soda Butte Creek using field data from a previous sediment tracer study (Legleiter and Lea, 2015). However, unlike past studies employing this method (Ham and Church, 2000; Gaeuman et al., 2003), Soda Butte Creek does not have an obvious zero-transport boundary condition. Minimum estimates of the transport rate could be obtained following Eaton and Lapointe (2001), where the budget is constrained so none of the transport rates are negative.

4.4. Caveats and sources of uncertainty associated with mean stream power calculation

Calculated $\omega$ values at $Q_{\text{MED}}$ support previous studies that found that stream power is heterogeneous even at short spatial distances and does not vary linearly downstream (Lecce, 1997; Knighton, 1999; Fosnadt, 2003; Vocal Ferencevic and Ashmore, 2012). However, this study assumed that flows equaling or exceeding $Q_{\text{MED}}$ occupy the entire bankfull channel. Because no imagery at a discharge similar to $Q_{\text{MED}}$ was available to verify this inference, $\omega$ likely was either over- or under predicted because of the width at $Q_{\text{MED}}$. Not matching the estimated bankfull width derived from the classified images. A potential solution to this problem would be to estimate the bankfull width used in stream power calculations from an empirical relationship between $Q_{\text{MED}}$ and width (Bizzeti and Lerner, 2013). However, this approach would be difficult to implement on Soda Butte Creek because of the variety of channel planforms. The cross sections measured in 2007 could also be used to calculate width...
as a function of $Q$, as a flow resistance equation such as Manning's could be used to determine the bankfull discharge for various channel morphologies.

While $\omega$ and estimated volumes of $E$, $D$, and $\Delta V$ were spatially averaged laterally and over the length of the budget cells, sediment transport and channel change are very localized processes that occurred at a sub-budget cell scale and were not detectable by the methods used in this study. Large amounts of geomorphic work could occur but go undetected because of compensating scour and fill, which indicates that Soda Butte Creek overall may be dynamically stable in more laterally active parts of the channel and stably dynamic where the channel is laterally confined.

The scour and fill that went undetected by the spatially averaged methods employed in this study would be driven by local fluid forces and variations in grain size. Two locations with the same slope and discharge would have the same $\Omega$, but differences in channel morphology could lead to dissimilar sediment response (Ferguson, 2003; Eaton et al., 2006). For example, near the apex of a meander bend the channel might have a roughly triangular shape with a deep pool along the outer bank and a relatively steep slope up to a point bar on the inside of the bend; for such a geometry, much of the cross section would be deep enough at $Q_{MED}$ to entrain sediment. However, a channel with a wide trapezoidal or rectangular cross section will not experience as significant an increase in depth as discharge increases, meaning local shear stress would not be as great. Thus, we can think of the V-shaped channel as having a more effective width for sediment transport than the flat and wide cross section. An important aspect of the resisting framework that also varies spatially along the river is the sediment grain size distribution. This study applied the same value, the median of $D_{50}$ values from Wolman pebble counts conducted throughout the study area, to all budget cells, but in reality variations in particle size along Soda Butte Creek would have dictated where $\omega$ exceeded $\Omega$, and subsequently affected our calculations of $E$. A more rigorous assessment could use a DEM to predict along-channel changes in median bed grain size, following the approach of Snyder et al. (2013), and ideally would quantify the uncertainty associated with these predictions by comparing estimated particle sizes to field measurements. The inability of the spatially averaged stream power and sediment budget approach to capture this variability in flow strength and sediment transport highlights the need to measure and analyze channel form at a high spatial resolution (Fonstad and Marcus, 2010; Carboneau et al., 2012).

4.5. Implications of auto- and cross-correlation results

Autocorrelations for $E$, $D$, $\Delta V$, and $<P>$ indicated that cells nearest to budget cell i had strong correlations but then decreased moving downstream. The lack of statistical significance beyond 4–7 budget cells for $E$, $D$, and $\Delta V$ or 8 budget cells for $<P>$ was a reflection of the heterogeneous planform of Soda Butte Creek along the 8-km study reach. The inability of this simple statistical approach to examine downstream changes in channel morphology again points to the need to measure the morphology of small, dynamic rivers such as Soda Butte Creek at high spatial resolution. Larger rivers or channels with a consistent, regular planform, such as a classic pool–riffle sequence, might have stronger correlations at set intervals downstream (Wilkinson et al., 2004).

The inconsistent relationships between $\Delta \omega / \delta s$ and $\epsilon_\omega$ values and $D$, $E$, and $\Delta V$ responses could be, at least in part, a consequence of the numerous assumptions used to develop the morphologic sediment budget and stream power maps; these conceptual and methodological limitations might have obscured any relationships that existed. Similarly, the lack of significant correlations could reflect the local, sub-budget cell scale nature of the underlying sediment transport processes and variations in resisting forces such as bank erodibility. These complications implied that consistent results could not be obtained when aggregating over larger areas. In a small, wandering gravel-bed river like Soda Butte Creek, even moderate 1-m² spatial resolution might not be sufficient to detect local, but cumulatively significant, changes. The lack of strong relationships between fluid driving forces and morphologic change also highlights the natural variability of complex river response to fluctuations in discharge and sediment compared to predictions of process and form (Wohl, 2013).

4.6. Applicability of the stream power gradient framework

In this study, various methodological limitations associated with the stream power gradient framework contributed to weak local and lagged cross-correlations between stream power gradients and sediment responses on Soda Butte Creek. The utility of this framework also was limited, however, by the unique characteristics of this dynamic, gravel-bed river. In this section, we attempt to generalize the SPG framework by identifying specific river attributes that might increase the likelihood of obtaining strong correlations between $\Delta \omega / \delta s$ and $E$, $D$, and $\Delta V$. Certain aspects of the framework will remain limitations for all types of rivers. For example, changes in bed elevation within the active channel cannot be detected using the SPG framework as implemented in this study, which considered only lateral channel shifting and representative bank and bar heights to convert areas of change to volumes of sediment. Rivers in which large amounts of sediment are stored and/or remobilized within the active, low-flow channel will have more undetected deposition and erosion, thus limiting the utility of this approach. Measuring bed elevations via passive topographical retrieval or bathymetric LiDAR could address this limitation of the SPG framework.

Soda Butte Creek’s modest size might have been another factor leading to poor cross-correlations between $\Delta \omega / \delta s$ and $E$, $D$, and $\Delta V$. The SPG framework would be expected to yield improved results in larger rivers in which sediment transport processes are expressed over larger spatial scales readily detectable by image data of a given resolution (i.e., 1 m²).

Smaller streams like Soda Butte Creek are less conducive to application of the SPG framework because sediment transport and channel change are more likely to occur at a sub-pixel scale. Since image resolution is a characteristic of the method rather than an inherent property of the river, the use of images with finer spatial resolution might lead to greater insight.

Another river attribute that might influence the utility of the SPG framework is the heterogeneity of bars and banks. Rivers in which gravel bars and vegetated floodplains can be differentiated easily using Random Forest classification and have a small range of heights relative to the channel bed are likely to produce stronger correlations between $\Delta \omega / \delta s$ and $E$, $D$, and $\Delta V$. In addition to spatial resolution, another image characteristic that influences the utility of the SPG framework is the number and wavelengths of spectral bands available for classifying land cover types. Smaller standard deviations of bank and bar heights would reduce uncertainty because the distribution of heights is more closely centered around the representative median value. Although the land cover classes identified along Soda Butte Creek were distinct from one another, the river was not ideally suited to the SPG framework because a broad range of measured bank heights lead to large uncertainties in calculated erosion and deposition volumes.

Correlations between $\Delta \omega / \delta s$ and $E$, $D$, and $\Delta V$ would be expected to improve in rivers experiencing relatively small amounts of in-channel scour and fill because these changes in bed elevation cannot be detected by the SPG framework as implemented herein. In contrast, the utility of our approach will increase where lateral erosion of bars and banks is more extensive and coarse sediment is deposited on newly formed bars downstream. Conversely, our methods cannot account for erosion or deposition occurring on the active channel bed or on existing bars or floodplains unless sediment transfer is manifested as a change in the areal extent of these features.

The proportion of sediment transported as bedload is another factor influencing the utility of the SPG framework. Both erosion and deposition of coarse bed material could have a measureable morphologic expression detectable in image time series, so rivers dominated by bed
material load might be expected to have stronger correlations between \( \text{d} \omega/\text{d}s \) and \( E, D, \) and \( \Delta V \). Conversely, finer-grained sediment transported in suspension is not accounted for by these methods. A partial solution to this problem would involve measuring the percentage of fines in exposed banks and using this value to reduce the representative height to include only the coarse sediment that might result in detectable deposition downstream. The proportion of fines could be used to approximate the fraction of the volume associated with an eroded bank expected to be transported out of the study area as suspended load. Field data on the percentage of fines in banks was not available for Soda Butte Creek, and the lack of such information might have contributed to the poor correlations observed in this study. Similarly, rivers with minimal variations in bank erodibility might be expected to have stronger correlations between \( \text{d} \omega/\text{d}s \) and \( E, D, \) and \( \Delta V \) because channel response to the same stream power gradient may be quite different in locations with distinct levels of bank erodibility. Again, Soda Butte Creek was not ideal in this regard because banks were more erodible in the upper, dry meadow reach than in the lower wet meadow reach.

In addition, the range of morphologies present along Soda Butte Creek further reduced the likelihood of obtaining strong correlations between \( \text{d} \omega/\text{d}s \) and \( E, D, \) and \( \Delta V \) using the SPG framework. This morphologic diversity created a greater range of bank and bar heights, which in turn led to greater uncertainty in calculated volumes of \( E, D, \) and \( \Delta V \). Rivers with a more homogenous morphology are better-suited to the SPG framework and thus more likely to yield stronger cross-correlations. Another important consideration is the extent to which the river of interest maintains a consistent gross morphology even when the channel is dynamic on a local, short-term basis; a change in the overall planform or channel pattern during a study would lead to weaker correlations between \( \text{d} \omega/\text{d}s \) and \( E, D, \) and \( \Delta V \). Such a wholesale shift in channel form might have occurred along Soda Butte Creek between the 1994 and 2001 images because of the two largest peak discharges on record during 1996 and 1997, which also featured long durations of high flow. While greater amounts of energy expenditure above a critical threshold might be expected to induce significant channel change, channels that maintain the same gross channel pattern even when impacted by such extreme events should show stronger correlations between stream power gradients and sediment flux.

5. Conclusions

This study assessed relationships among channel change, volumes of erosion, deposition, and net sediment flux, spatial gradients in stream power, and average excess energy expenditure per unit bed area. The geomorphic complexity of Soda Butte Creek precluded strong correlations between the river’s driving forces and sediment flux. Inability to link local, sub-budget scale variability highlighted the assumptions and limitations involved in processing data that was not of sufficient spatial resolution to capture the underlying transport processes. However, the results of this study provided insight on the spatial distributions of stream power and channel change between 1994 and 2012 that would not have been feasible to acquire using traditional field-based approaches.

The lack of strong relationships observed in this study indicated that the spatially averaged morphologic approach for calculating mean stream power and net sediment fluxes might not have been capable of characterizing the complexity and fine-scale variability present in a dynamic natural river. While the moderate spatial resolution used here was not sufficient to relate local flow conditions to morphologic changes, these results provide justification for further development and application of methods for acquiring very-high resolution flow and topography data. Tools such as repeat LiDAR coverage, Structure for Motion, and Terrestrial Laser Scanning have shown the ability to acquire higher resolution data that could be compared to the results of this study to better understand the errors associated with the moderate resolution approach we employed. However, because of high cost (e.g., LiDAR) and/or minimal testing (e.g., UAVs), data acquired by these sources are still not common, and long-term historical data sets for studying rivers are limited to aerial photographs and field surveys. Thus continued research into methods of relating fluvial forms and processes using moderate resolution, spatially averaged approaches remains relevant.

### Notation

- \( A \): drainage area \([\text{km}^2]\)
- \( D \): gross deposition \([\text{m}^3]\)
- \( E \): gross erosion \([\text{m}^3]\)
- \( F_n \): feature occurrence for locational probability
- \( g \): acceleration of gravity \([\text{m} \text{s}^{-2}]\)
- \( i \): budget cell index
- \( j \): budget cell lag
- \( m \): length of record for locational probability \([\text{yr}]\)
- \( n \): distance toward banks in a channel-fitted coordinate system \([\text{m}]\)
- \( P \): locational probability
- \( <P> \): average locational probability
- \( Q \): discharge \([\text{m}^3 \text{s}^{-1}]\)
- \( Q_d \): mean daily discharge \([\text{m}^3 \text{s}^{-1}]\)
- \( Q_{MED} \): median annual peak discharge \([\text{m}^3 \text{s}^{-1}]\)
- \( r \): correlation coefficient
- \( s \): distance downstream along a channel-fitted coordinate system \([\text{m}]\)
- \( S_w \): slope \([\text{m} \text{m}^{-1}]\)
- \( t_r \): time interval between images \([\text{yr}]\)
- \( W_n \): total sediment flux \([\text{m}^3]\)
- \( w \): channel width \([\text{m}]\)
- \( \alpha \): coefficient for Eq. (6)
- \( \beta \): coefficient for Eq. (6)
- \( \Delta V \): net sediment flux \([\text{m}^3]\)
- \( \epsilon \): excess energy per unit bed area over \( \epsilon_k \) \([\text{J}]\)
- \( \epsilon_a \): average excess energy per unit bed area \([\text{J}]\)
- \( \epsilon_c \): cumulative excess energy per unit bed area \([\text{J}]\)
- \( \rho \): density of water \([\text{kg m}^{-3}]\)
- \( \Omega \): cross-sectional stream power \([\text{W m}^{-1}]\)
- \( \omega \): mean stream power \([\text{W m}^{-2}]\)
- \( \epsilon_k \): critical mean stream power \([\text{W m}^{-2}]\)
- \( \text{d} \omega/\text{d}s \): mean stream power gradient \([\text{W m}^{-2}/\text{m}]\)

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