Assessment and Characterization of Ephemeral Stream Channel Stability in the Grand Valley, Colorado, 2018-22

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Abstract

The purpose of this study is to provide information regarding the stability of ephemeral streams on the north side of the Grand Valley, Colorado. The ungaged ephemeral streams in this semiarid region are of particular interest because (1) the underlying bedrock geology, Mancos Shale, is a sedimentary rock deposit that has been identified as a major contributor of salinity to the Colorado River and (2) despite infrequent flows of short duration, monsoon derived floods in these ephemeral streams can carry substantial amounts of sediment downstream, affecting up and downstream banks and channel cross sections. The study area is of interest as salinity, or the total dissolved solids concentration, in the Colorado River causes significant economic damages in the United States and geologic sources are a significant contributor of Upper Colorado River Basin dissolved-solid. In an effort to minimize salt contributions to the Colorado River from public lands administered by the Bureau of Land Management (BLM) a comprehensive three-pronged salinity control approach is being used which incorporates (1) controlling point sources of salinity; (2) controlling nonpoint sources of salinity; and (3) preventing nonpoint sources of salinity from persisting.

In 2018, the U.S. Geological Survey (USGS), in cooperation with BLM, began an assessment of ephemeral streams located in the north side of the Grand Valley, Colorado, to characterize stream channel stability. The USGS developed a method for automatically extracting channel cross-section geometry from existing remotely sensed terrain models. Based on estimated flood stage and surrogate streamflows, hydraulic characteristics were calculated. Furthermore, the channel geometries and hydraulic characteristics were used to estimate channel stability utilizing a statistical model.

In this ongoing study, cross-section stabilities were determined from a stream channel stability assessment for a subset of 1,406 visited locations out of a desired 13,415 cross sections which were delineated from remotely sensed terrain models. The application of Manning's resistance equation in combination with multiple Logistic Regression models demonstrated that channel stability can be estimated with an 0.85 goodness of fit for a validation dataset when using a combination of drainage area, width to depth ratio, sinuosity, and shear stress as the explanatory variables. Stream channel stability was extrapolated for the remaining 13,415 unvisited cross sections using the multiple Logistic Regression model and defined explanatory variables. Mapping the ephemeral streams and their associated stabilities could be used to support BLM prioritization of areas for remediation or changes in management strategies to reduce sediment and salinity loading to the Colorado River.

Keywords: Ephemeral Streams, Channel Stability, Logistic Regression

Introduction

Non-perennial streams can flow either seasonally (intermittent), or only briefly after rain or snowmelt events (ephemeral), and are present across all global continents, ecoregions, and climate types. Non-perennial streams constitute over half the global stream network length (Messager and others, 2021). They make up approximately 59 percent of all streams in the United States (excluding Alaska) and over 81 percent in the arid and semi-arid Southwest (Arizona, New Mexico, Nevada, Utah, Colorado, and California) according to the U.S. Geological Survey (USGS) National Hydrography Dataset (Levick and others, 2008). Hydrological and ecological research has predominantly focused on perennial waters, in part because gage networks are biased toward larger rivers (Zimmer and others, 2020). However, non-perennial streams have garnered increasing consideration in recent years (Leigh and others, 2016; Allen and others, 2020; Shanafield and others 2020, 2021) and this attention will likely continue in growth as the abundance of non-perennial streams is predicted to increase due to climate change and land use alterations as these systems experience increased drying (Palmer and others, 2008; Larned and others 2010; Jaeger and others, 2014; Datry and others, 2018; Ward and Walsh, 2020). Utilizing USGS streamgage data, Zipper and others (2021) illustrated this trend is already in effect in the arid and semi-arid Southwest United States where the degree of intermittency in most streams has been increasing over the past 30 years. Additionally, the study highlighted the critical need for adequate non-perennial stream assessments as streamgages are typically installed in perennial streams to support human-oriented water needs, including allocation of water resources, flood hazard mitigation, and riverine navigation.

The Grand Valley in western Colorado is located in the semiarid Southwest United States. The north side of the Grand Valley has many ungaged ephemeral streams which are of particular interest because (1) the underlying bedrock geology, Mancos Shale, is a sedimentary rock deposited in a shallow sea environment during the Late Cretaceous epoch and has been identified as a major contributor of dissolved mineral salts to the Colorado River (Whittig and others, 1982; Weltz and others, 2014) and (2) despite infrequent flows of short duration, monsoon derived floods in ephemeral streams can transport substantial amounts of sediment downstream (Hassan, 1990). These are important because salinity, or the total dissolved solids concentration, in the Colorado River causes an estimated $300 to $400 million per year in economic damages in the United States (Reclamation 2001). Dissolved solids in water occur naturally due to weathering and dissolution of minerals in soils and rocks; however, various anthropogenic activities can increase dissolved-solid loading above natural levels (Anning and others, 2010). Geology, land cover, land-use practices, and climate are factors known to affect dissolved-solids loading to streams (Kenney and others, 2009). To address these challenges, the Colorado River Basin Salinity Control Forum (CRBSCF) was established in 1973 (CRBSCF, 2014) to enhance and protect the quality of water in the Colorado River for use in the United States and Mexico, in accordance with the 1972 Clean Water Act and the Salinity Control Act of 1974 (Reclamation, 2001).

Within the Colorado River Basin, the Bureau of Land Management (BLM) administers approximately 53 million acres of public lands and approximately 7.2 million of those acres contain saline soils (BLM, 1987, Boyd and Green, 2018). Within these lands, nonpoint sources of salt include surface runoff, eroded soils, stream sediment, and groundwater discharge to streams, with salt concentrations being the greatest from land with marine shales and mudstones such as the Mancos Shale (Bentley and others, 1978). Within the Colorado River Basin, highly saline soils generally occur in rangeland areas that receive low annual precipitation (less than 20 centimeters [cm]). Although salt concentration can be very high in runoff waters from these lands, the frequency and volume of runoff is very low due to the ephemeral nature of the stream system (Bentley and others, 1978). Regardless, runoff from highly to moderately saline soils in the Upper Colorado River Basin contributes approximately half of the annual salt load from BLM administered public lands (Bentley and others, 1978; BLM, 1987; BLM, 2004) and it is estimated that 62 percent of Upper Colorado River Basin dissolved-solid loads originate from geologic sources (Miller and others, 2017).

In an effort to minimize salt contributions to the Colorado River from public lands administered by the BLM a comprehensive three-pronged salinity control approach is being used which incorporates (1) controlling point sources of salinity, such as discharges from abandoned wells and mines; (2) controlling nonpoint sources of salinity, such as by reducing sediment transport from past activities through a number of land management programs and watershed restoration activities; and (3) preventing nonpoint sources of salinity from ongoing, authorized activities through land use planning, permit stipulations, best management practices, and related conservation actions (Boyd and Green, 2018). Ephemeral streams are one salt transport mechanism in arid rangelands, where salt may be transported either in solution or attached to eroded soil particles. Salt loading in these environments is closely associated with sediment loading (Jackson and others, 1985; Schumm and Gregory, 1986; BLM, 1987; Gellis and others 1991; Reclamation, 2001). Any practices that reduce erosion or store sediments outside of the active channel in highly saline arid landscapes, especially in headwater areas, could affect the retainment of salt from these associated sediments.

In 2018, the USGS, in cooperation with BLM, began an assessment of ephemeral streams located on the north side of the Grand Valley in Colorado (fig 1), to characterize stream channel stability. The ephemeral streams within the study area lacked sediment and hydrological data, so rather than implementing a sediment transport model or hydraulically driven analysis to assess their stability, channel geometries and surrogate streamflows were utilized. Channel cross-section geometries were acquired from existing remotely sensed terrain models (USGS, 2019a), and calculated hydraulic characteristics were based on surrogate StreamStats streamflows (USGS, 2019b). Instead of relying on available software, such as HEC-RAS (HEC, 2021), to manually extract channel cross sections and generate associated channel geometries and hydraulic characteristics on more than ten thousand stream channel locations, the USGS utilized R code and RStudio statistical software version 4.2.2 (RStudio Team, 2022) to automate the process. Utilizing a statistical model, the channel geometries and hydraulic characteristics were used as predictor variables to estimate the probability of channel stability for the ephemeral streams. The probability of channel stability in this arid rangeland was mapped and areas with low probability of channel stability could be used by BLM to evaluate and prioritize areas to target for remediation or changes in management strategies to reduce sediment and salinity loading to the Colorado River.

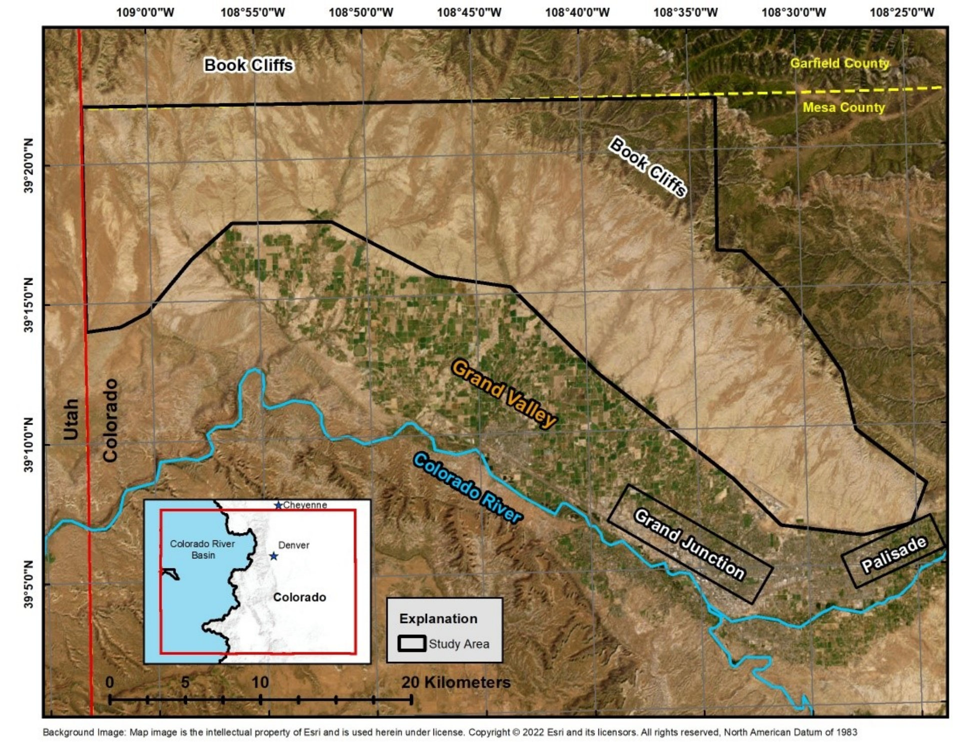

Figure 1: Areal image showing the study area (light gray shading) near Grand Junction, Colorado.

Methodology

Cross-section stabilities were determined from a stream channel stability assessment for a subset of 1,406 visited locations out of a desired 13,415 cross sections which were delineated from remotely sensed terrain models. To predict whether the remaining unvisited ephemeral stream cross sections are stable or experiencing erosion, multiple Logistic Regression models were used. In statistics, a regression model is a method by which one variable is explained or understood on the basis of one or more other variables (Hilbe, 2009). The variable that is being explained is called the dependent, or response, variable; the other variables used to explain or predict the response are called independent variables. Typically independent variables are simply referred to as predictors or explanatory variables. For this study, the variable being explained was cross-section stabilities and the explanatory variables included 18 independent channel geometry and hydraulic characteristic, as well as road proximity and density information (Table 1). All data associated with this study, including cross-section profiles, StreamStats streamflows, Manning's N values, channel geometry characteristics and hydraulics, and channel stabilities are available in a USGS data release (Homan, 2023).

Table 1. Explanatory variables used within the multiple Logistic Regression models.

Streamflow	Average velocity	Specific stream power
Drainage area	Channel top width	Shear stress
Channel bed slope	Maximum depth of water	Froude number
Sinuosity	Wetted perimeter	Width to depth ratio
Manning's n	Hydraulic radius	Road Proximity
Streamflow area	Total stream power	Road density

To calibrate the Logistic Regression models and assess the outputs of stream channel stability, a ground truthing component was needed. Within the study area, channel stability was assessed at 1,406 cross sections within 48 ephemeral stream channels. The field-based channel stability observations were split into calibration and validation datasets and used to evaluate the predictive powers of different combinations of the 18 explanatory variables. Constructed Logistic Regression models predicted channel stability as a function of the explanatory variables used, with not all variables providing the same predictive powers. Optimization of a model is achieved when a model provides the best predictive powers with the fewest explanatory variables. There are various machine learning methods to select, adjust, or change the explanatory variables used in the multiple Logistic Regression models, including but not limited to stepwise, bootstrapping, LASSO, and dominance analysis (Azen and Traxel, 2009; Bursac and others, 2008; Zhang and other, 2015. The four machine learning methods were used to assist the explanatory variable selections. The Logistic Regression outputs are coded as 0 or 1, where 1 indicates that the outcome of interest is present (for example, active erosion), and 0 indicates that the outcome of interest is absent (for example, stable or no erosion). If p is the probability that the outcome is 1, the multiple Logistic Regression model can be written as follows (Helsel and others, 2020):

$$\hat{p} = \frac{\exp\left(b_0+b_1X_1+b_2X_2+\cdots+b_pX_p\right)}{1+\exp\left(b_0+b_1X_1+b_2X_2+\cdots+b_pX_p\right)} \quad \text{(Eq. 1)}$$

where:

$\hat{p}$ = the expected probability that the outcome is present,

exp is an abbreviation for exponential,

X_1 through X_p are the distinct independent variables, and

b_1 through b_p are the regression coefficients.

The modeled probabilities could not be directly compared to the stability assessments within the validation datasets, so probabilities over 50 percent were assigned a binary value of active, whereas probabilities less than 50 percent were defined as stable. Validation of the model's predictive abilities were based on goodness-of-fit r-squared (r2), Akaike information criterion (AIC) and McFadden's pseudo-r-squared (pseudo r2) values. Larger r2 values represent smaller differences between the observed data and the fitted values, and a better fit model (Healy, 1984), lower AIC values indicate a better-fit model (Kenney, 2015), and McFadden's pseudo r2 values 0.2 or greater indicate good-to-excellent model fit (Lane and others, 2009).

Using the top performing multiple Logistic regression model, stream channel stability was extrapolated for 13,415 unvisited cross sections. The modeled erosion probabilities for all cross sections were subsequently mapped in Aeronautical Reconnaissance Coverage Geographic Information System (ArcGIS) software version 10.8.1 (esri 2020) to identify locations of instability and where remediation or change to management strategies could potentially reduce sediment and salinity loading downstream.

Results

Based on the stream channel stability assessments, cross-section stabilities were known for the subset of 1,406 visited locations but needed to be estimated at 13,415 cross sections with explanatory variables. Multiple Logistic Regression models were utilized to extrapolate stream channel stability to the unvisited cross sections. Working with the 18 explanatory variables (Table 1) and four machine learning methods (stepwise, bootstrapping, LASSO, and dominance analysis) to assist the explanatory variable selections, 28 explanatory variable combinations were designated. Of the 28 multiple Logistic Regression models (explanatory variable combinations), the top performing model, “glm_20” (where “glm” stands for generalized linear model), had the highest r2 value, lowest AIC value, and largest pseudo r2 value is presented in Table 2.

Table 2. Goodness-of-fit r-squared (r2), Akaike information criterion (AIC), and McFadden’s pseudo-R-squared (pseudo r^2), for the top generalized linear model (GLM) using drainage area, width to depth ratio, sinuosity, and shear stress as the explanatory variables.

r^2	AIC	pseudo r^2	GLM_20
0.845	1121	0.16	Drainage Area + Sinuosity + Shear Stress + Width to Depth Ratio

For the stream channel stability validation dataset, which consisted of 422 cross sections dispersed throughout the study area, the glm_20 model correctly estimated channel stability with an 0.845 goodness of fit when using a combination of drainage area, width to depth ratio, sinuosity, and shear stress as the explanatory variables (Table 2). Using this top performing multiple Logistic Regression model (glm_20), stream channel stability was extrapolated for the remaining unvisited cross sections.

Figure **2** shows the modeled erosion probabilities (0 to 100 percent) mapped at all 13,415 cross sections along the 48 ephemeral streams within the north side of the Grand Valley. The erosion probabilities are modeled confidence levels that the cross sections are experiencing erosion, with no indication about the severity or magnitude of erosion. Based on the criteria that cross sections with erosion probabilities over 50 percent are active and cross sections with erosion probabilities less than 50 percent are stable, a total of 10,080 cross sections, or roughly 75 percent, are modeled as active.

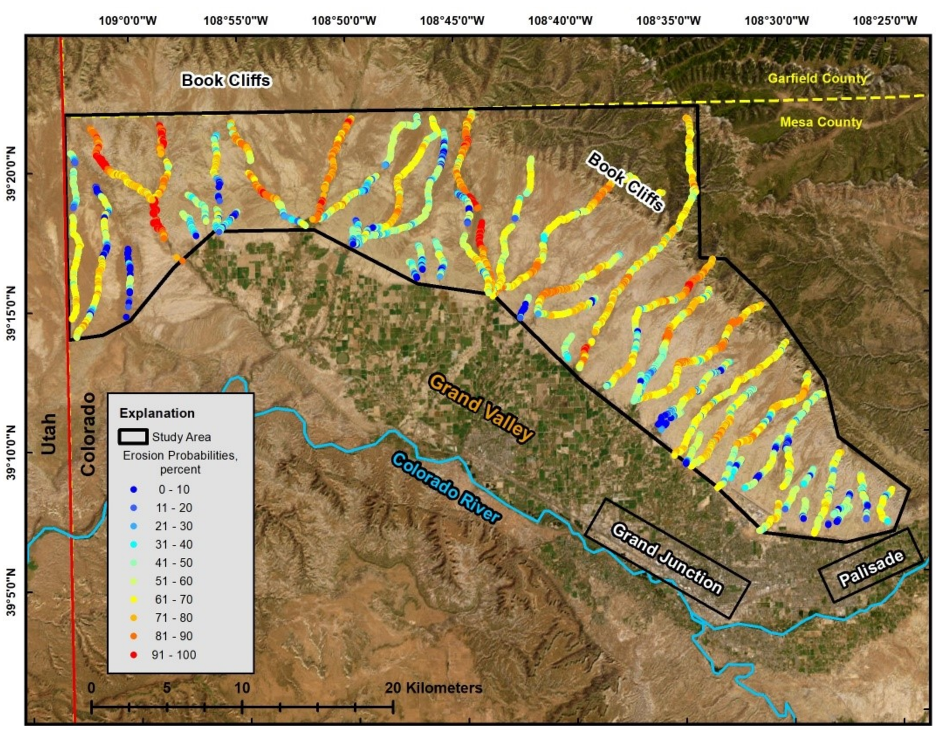

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Figure 2. Multiple Logistic Regression erosion probabilities for the 13,415 cross sections within Grand Valley, Colorado (Homan, 2023).

Based on the evaluation of erosion probabilities within the validation dataset, it was recognized that active erosion in smaller cross sections (for example, 1-m wide and a few centimeters deep) have less potential sediment compared to larger cross sections (for example, 10-m wide and 2-m deep). The concept of a larger area having more sediment potential is not revolutionary, but it is especially true for ephemeral streams, which are not sediment supply limited like perennial channels (Reid and Laronne, 1995), therefore, larger cross-sectional surface areas have a greater amount of potential sediment for transport. To account for potential sediment within active cross sections, the erosion probabilities were weighted (multiplied) by the cross-sectional streamflow areas (Homan, 2023). The resultant high-resolution map (Figure 3
Figure 2) of weighted erosion probability could help to prioritize specific areas for more

intensive study. The weighted erosion probabilities consider the multiple Logistic Regression

modeled confidence levels as well as the amount of potentially available sediment. Unlike figure

Figure 2, which illustrates three fourths of the study area as having active erosion, fewer stream channels are identified (red/orange/yellow) as having greater potential levels of sediment and salinity loading to the Colorado River in Figure 3.

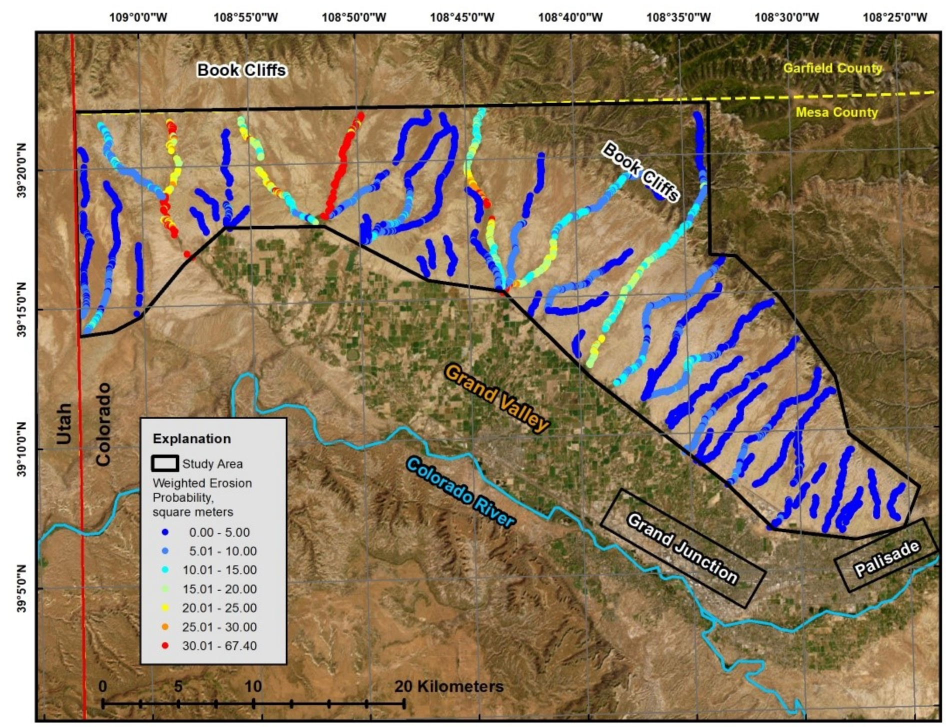

Figure 3. Map of cross section streamflow area weighted (multiplied by the cross-sectional streamflow areas) erosion probabilities for the 48 stream channels using 13,415 cross sections in Grand Valley, Colorado (Homan, 2023).

Conclusion

The Grand Valley in western Colorado is located in the semiarid Southwest United States within the Upper Colorado River Basin; an area which includes many ungaged ephemeral streams that are of particular interest because (1) the underlying bedrock geology, Mancos Shale, is a sedimentary rock deposited in a shallow sea environment during the Late Cretaceous epoch and has been identified as a major contributor of dissolved mineral salts to the Colorado River and (2) despite infrequent streamflow events of short duration, monsoon derived floods in ephemeral streams can carry substantial amounts of sediment downstream (Hassan 1990). These points of interest are important because salinity, or the total dissolved solids concentration, in the Colorado River causes an estimated $300 to $400 million per year in economic damages in the United States (reclamation, 2017), and it is estimated that 62 percent of Upper Colorado River Basin dissolved-solid loads originate from geologic sources (Miller and others, 2017). Salt loading in these environments is closely associated with sediment loading (Jackson and others, 1985; Schumm and Gregory, 1986; BLM, 1987; Gellis and others 1991; BOR, 2001). Any practices that reduce erosion and store sediment in highly saline arid landscapes, especially in headwater areas, could have the effect of retaining salt in the trapped sediment. In an effort to minimize salt contributions to the Colorado River from public lands administered by the BLM, a comprehensive salinity control approach is used to reduce nonpoint sources of salinity through cost-effective land management techniques and practices (BLM, 2004; Boyd and Green, 2018).

In 2018, the USGS, in cooperation with the BLM, began an assessment of ephemeral streams located in the north side of the Grand Valley, Colorado, to characterize stream channel stability and identify mechanisms driving erosion. In doing so, the USGS developed a method using R code and RStudio statistical software for automatically extracting channel geometries from existing remotely sensed terrain models and based on estimated flood stage streamflows, and hydraulic characteristics were calculated. Furthermore, utilizing a statistical model, the channel geometries and hydraulic characteristics were used to estimate channel stability at individual cross sections for the ephemeral streams.
Based on a stream channel stability assessment, cross-section stabilities were known for a subset of 1,406 visited locations but desired for 13,415 cross sections which were delineated from remotely sensed terrain models. The application of Manning's resistance equation (Manning, 1891) in combination with multiple Logistic Regression models demonstrated that channel stability can be estimated with an 0.85 goodness of fit for a validation dataset when using a combination of drainage area, width to depth ratio, sinuosity, and shear stress as the explanatory variables. Using the multiple Logistic Regression model and defined explanatory variables, stream channel stability was extrapolated for the remaining unvisited cross sections. Maps of the ephemeral streams and their stabilities in this arid rangeland, that is underlain by saline rich Mancos Shale, could be used to prioritize areas for remediation or changes in management strategies to reduce sediment and salinity loading to the Colorado River.

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