The importance of base flow in sustaining surface water flow in the Upper Colorado River Basin

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Abstract The Colorado River has been identified as the most overallocated river in the world. Considering predicted future imbalances between water supply and demand and the growing recognition that base flow (a proxy for groundwater discharge to streams) is critical for sustaining flow in streams and rivers, there is a need to develop methods to better quantify present-day base flow across large regions. We adapted and applied the spatially referenced regression on watershed attributes (SPARROW) water quality model to assess the spatial distribution of base flow, the fraction of streamflow supported by base flow, and estimates of and potential processes contributing to the amount of base flow that is lost during in-stream transport in the Upper Colorado River Basin (UCRB). On average, 56% of the streamflow in the UCRB originated as base flow, and precipitation was identified as the dominant driver of spatial variability in base flow at the scale of the UCRB, with the majority of base flow discharge to streams occurring in upper elevation watersheds. The model estimates an average of 1.8 x 10¹⁰ m³/yr of base flow in the UCRB; greater than 80% of which is lost during in-stream transport to the Lower Colorado River Basin via processes including evapotranspiration and water diversion for irrigation. Our results indicate that surface waters in the Colorado River Basin are dependent on base flow, and that management approaches that consider groundwater and surface water as a joint resource will be needed to effectively manage current and future water resources in the Basin.

1. Introduction

The Colorado River is the most overallocated river in the world [Christensen et al., 2004], with water demand projected to be greater than supply by approximately 4 x 10⁹ m³ in the year 2060 [U.S. Bureau of Reclamation, 2012]. This projected imbalance and related projected declines in streamflow [Christensen and Lettenmaier, 2007; McCabe and Wolock, 2007; Barnett and Pierce, 2009; Reynolds et al., 2015] are driven in large part by more extreme future drought conditions [Cayan et al., 2010] and projected population growth. The basin currently supports 50 million people, and the population in the seven states that rely on Colorado River water (note that not all growth in these states is sustained by allocations from the Colorado River) is expected to increase by 23 million people between 2000 and 2030 [Gleick, 2010; Gober and Kirkwood, 2010]. Historically, management of water resources in the Colorado River Basin focused largely on surface water [U.S. Bureau of Reclamation, 2007]. However, surface water flow is often sustained by groundwater discharge to streams. This indicates that groundwater and surface water are interconnected [Winter et al., 1998], and there is growing recognition that, in light of recent droughts and predicted changes in climate and human use of water, there is an urgent need to think of and manage groundwater and surface water as a single resource [Famiglietti, 2014; McNut, 2014]. This will require the continued development of methods to quantify the amount and spatial variability of this joint groundwater-surface water resource.

Hydrologists have long recognized the interconnected nature of groundwater and surface water. An excellent example of this is the development and use of hydrograph separation methods to identify different flow components contributing to streamflow, beginning with Boussinesq [1877]. Hydrograph separation techniques range in complexity from graphical approaches that separate the hydrograph into base flow (a proxy for groundwater discharge to streams) and runoff components using only a record of stream discharge (e.g., recession curve [Barnes, 1939] or digital filter [Nathan and McMahon, 1990] methods), to two-component chemical mass balance separations that require stream discharge and chemistry data [Pinder and Jones, 1969], and to many-component separations that rely on measures of stream discharge, chemistry
in potential source waters, and multivariate statistical methods [Christopherson and Hooper, 1992]. In a comparison of seven commonly used graphical hydrograph separation methods, it was concluded that Eckhardt's recursive digital filter method [Eckhardt, 2005], for which it is possible to assess the analytical sensitivity of the digital filter parameters [Eckhardt, 2012], was found to be the most hydrologically plausible separation approach [Eckhardt, 2008]. Partington et al. [2012] compared base flow estimates from graphical hydrograph separation approaches with base flow obtained from an integrated surface water-groundwater flow model and found that the base flow estimates from graphical approaches differed substantially from those derived using the numerical model. It has been argued that chemical mass balance approaches are more objective than graphical approaches because measured geochemical data provide a direct relation to physical and chemical processes and flow paths in the basin [Stewart et al., 2007; Zhang et al., 2013].

In snowmelt-dominated streams and rivers in the Upper Colorado River Basin (UCRB), it has been demonstrated that a specific type of chemical hydrograph separation—conductivity mass balance—that uses high-frequency specific conductance (SC) data as a chemical tracer is an effective approach for estimating base flow and runoff fractions of streamflow [Miller et al., 2014]. When SC is used to estimate base flow, the base flow represents the integrated SC signal from all high SC subsurface flow paths, including deep regional groundwater and shallow near-stream flow paths. While conductivity mass balance has been shown to be effective for estimating base flow in the UCRB, its application at large numbers of sites has been limited by a lack of high-frequency SC data. Regression modeling to generate continuous estimates of SC at sites that have only discrete SC data has been used to overcome this limitation, and has been shown to be useful for estimating base flow at such sites [Miller et al., 2015]. Subsequently, the regression approach has been used to estimate base flow at 229 sites in the UCRB where it is reported that, on average, among these sites, base flow contributes 48% of total streamflow [Rumsey et al., 2015], thus clearly demonstrating the importance of base flow for sustaining surface water flows.

Given the importance of base flow in sustaining streamflow, it would be useful to have spatially distributed estimates of the quantity of base flow to inform current and future use of water resources in the UCRB. For this reason, there is interest in using point estimates of base flow to estimate base flow at ungauged locations. While such approaches have been applied with graphical hydrograph separation methods to estimate base flow for the contiguous United States [Wolock, 2003; Santhi et al., 2008] and the entire globe [Beck et al., 2013], their application with conductivity mass balance has been limited by a lack of available conductivity mass balance estimates of base flow. The development of the aforementioned regression approach overcomes this limitation and provides a new opportunity to generate conductivity mass balance-derived base flow estimates at a large number of sites that can be used as calibration data to build models that predict conductivity mass balance-derived base flow estimates across large regions.

We used long-term mean annual conductivity mass balance-derived base flow estimates at 146 sites in the UCRB as calibration data to build a model that predicts long-term mean annual base flow across the Basin. Specifically, we adapted and applied the spatially referenced regression on watershed attributes (SPARROW) water quality model [Smith et al., 1997; Schwarz et al., 2006] to assess (1) the spatial distribution of base flow in the UCRB, including an estimate of the mean annual base flow that is delivered to the Lower Colorado River Basin, (2) the fraction of mean annual streamflow supported by base flow in the UCRB, and (3) estimates of and potential processes contributing to the amount of base flow that is lost after it has entered streams. We also compare the fraction of mean annual streamflow that is estimated to be base flow by the SPARROW model with estimates from a commonly used graphical hydrograph separation approach. Model results are interpreted in the context of natural and anthropogenic controls on base flow discharge to streams in the UCRB.

2. Methods
2.1. Site Description
The UCRB is defined as the drainage basin upstream of the Colorado River at Lee’s Ferry, AZ (USGS streamgage 0938000), and drains an area of $2.8 \times 10^5$ km$^2$, including portions of Wyoming, Utah, Colorado, Arizona, and New Mexico (Figure 1). Dominant geographic features include the western slope of the Rocky Mountains, ranging from the Wind River Range in the northeast part of the Basin to the San Juan Range in the southeast of the UCRB (Figure 1a). Much of the western boundary of the UCRB is bordered by the
Figure 1. Maps of the Upper Colorado River Basin showing (a) elevation, (b) average annual precipitation, (c) average annual temperature, and (d) 8 HUC4 watersheds (labeled by color) and 58 HUC8 watersheds (delineated by grey lines). Grey points in Figure 1d represent the locations of the monitoring stations used to estimate the base flow SPARROW model. The inset in Figure 1a shows the location of the UCRB in the continental United States.
Wasatch Mountain Range, with the Uinta Mountain Range running west-east in Utah, just south of the Wyoming border. Average elevation in the UCRB is 2087 m (range = 988–3,720 m), average annual precipitation is 370 mm (range = 130–1400 mm), and average annual temperature is 7.7°C (range = −1.8 to 16.9°C) (Figure 1; see supporting information for details on data sources). Given the large elevation and climate gradients in the UCRB, there are a diversity of landscapes, ranging from high-elevation alpine areas that receive most of their precipitation as snow, to lower, drier, and warmer areas of the Colorado Plateau. Major rivers in the UCRB include the Colorado, Green, Gunnison, San Juan, White, and Yampa Rivers. Much of the surface water flow in the UCRB is regulated, including the presence of large reservoirs, such as Lake Powell (capacity of 3.3 × 10^10 m^3), near the outlet of the UCRB.

Groundwater is present in the UCRB in numerous aquifers varying from shallow talus and colluvium and fractured bedrock in upland areas, to alluvial aquifers associated with streams and rivers, to large-scale Mesozoic and Paleozoic sedimentary rock aquifers in the Colorado Plateau. Base flow in upland aquifers is likely similar to flow systems described by Frisbee et al. [2011] who investigated a high-elevation alpine watershed in central Colorado, and identified groundwater contribution to streamflow as being a composite of shallow subsurface flow paths and larger-scale groundwater flow paths. The Mesozoic and Paleozoic aquifers are composed of extensive sandstones and limestones [Freethey and Cordy, 1991; Geldon, 2003] and form the groundwater flow systems throughout much of the lower-elevation portions of the UCRB. Here larger-scale, older, groundwater flow is likely the dominant component of base flow contribution to streamflow.

2.2. SPARROW Model

The SPARROW water quality model was adapted and applied to estimate mean annual base flow in the UCRB. Two separate, independent SPARROW models were developed—one for base flow and a separate model for total streamflow. The streamflow model was developed to allow for the prediction of base flow index (BFI, defined as the ratio of mean annual base flow to mean annual streamflow) values. SPARROW is a GIS-based hybrid statistical-deterministic model that uses nonlinear least squares (NLLS) regression with mass balance constraints to identify the spatial relationships between an observed mass of a constituent (in this case, mean annual base flow or total streamflow) and constituent sources, transport, and transformation processes (i.e., in-stream losses) in aquatic and terrestrial portions of a watershed under long-term steady state conditions. Specifically, the NLLS approach estimates parameter coefficients associated with the sources, transport, and transformation processes. The stream network routing built into the SPARROW model provides an explicit spatial structure that allows for mass balance constraints to be applied to the downstream transport of base flow.

SPARROW was chosen to model base flow and total streamflow in the UCRB because it is a simple, empirical watershed modeling tool that relates estimates of mean annual base flow or streamflow in a network of monitoring stations to watershed attributes. The steady state nature of the SPARROW model quantifies the long-term effects of watershed processes on base flow, but does not detect the effects of watershed processes that occur on short (less than annual) time scales that can be quantified with dynamic mechanistic models. This approach has value when estimating base flow at a large spatial scale, where the application of dynamic mechanistic models is limited by the extensive infrastructure and data needed to support such models. While SPARROW deemphasizes the quantification of fine-scale temporally dynamic processes that may be accounted for in dynamic mechanistic models, it allows for the construction of large-scale regional models in which mass balance constraints can be applied. The SPARROW model provides estimates of base flow in unmeasured locations via identification of statistical relationships between base flow and watershed characteristics as well as routing of base flow through the stream network. Further, SPARROW provides estimates of incremental and total mean annual base flow discharge to streams, which can then be used to estimate in-stream loss of base flow as it travels through the stream network (details provided in section 2.2.3).

The SPARROW model is built using (1) estimates of mean annual base flow obtained from conductivity mass balance hydrograph separation, which is explained below (for the base flow model) or measured mean annual streamflow (for the total streamflow model) at streamgages, which are used as model calibration data, (2) a hydrologic network of stream reaches through which the constituent is routed, and (3) spatially variable data on watershed characteristics that represent sources of base flow or total streamflow,
land-to-water delivery (i.e., transport) processes, and in-stream transformation processes. Importantly, the estimates of base flow used as calibration data were obtained from stream geochemical data (details provided in next section), as a preliminary step, which provides a direct relation between estimated base flow and physical and chemical processes and flow paths in the basin. Model estimated coefficients are then used within the routing constraints of the model to predict long-term mean annual base flow or streamflow in 10,789 subcatchments (reaches) of the UCRB. The governing equation that describes mean annual base flow (or mean annual streamflow) leaving reach \( i \) is given by equation (1):

\[
\text{Baseflow}_i = \left( \sum_{j \in \text{downstream}} \text{Baseflow}_j \right) \delta_i A[Z_i^f, Z_i^a; \theta_i, \theta_b] + \left( \sum_{n=1}^{N_n} S_n \times D_n(Z_{iD_n}; \theta_D) \right) A'[Z_i^f, Z_i^a, \theta_i, \theta_b]
\]

where the first summation term represents the base flow or total streamflow from all upstream contributing reaches \( j \) that are delivered to reach \( i \). \( \delta_i \) is the dimensionless fraction of upstream flux delivered to reach \( i \). \( \delta_i \) equals 1, unless there is a trans-basin diversion of water out of the reach. All major trans-basin diversions were accounted for in the model using the \( \delta_i \) term. \( A \) is the aquatic transport function, representing attenuation of base flow or total streamflow as it travels through the reach, and defines the fraction of base flow or total streamflow entering the upstream end of reach \( i \) that is delivered to the downstream end of reach \( i \). \( A \) is a function of stream (\( S \)) and reservoir (\( R \)) characteristics defined by vectors \( Z_i^f \) and \( Z_i^a \), with coefficient vectors \( \theta_i \) and \( \theta_b \). The second summation term represents the incremental base flow or total streamflow contributed in reach \( i \). \( S_n \) represents the specific sources of base flow or total streamflow in reach \( i \), with source-specific coefficient \( x_n \). \( D_n \) is the land-to-water delivery function, which along with \( x_n \) determines the base flow or total streamflow delivered to the stream in reach \( i \). \( D_n \) is a source-specific function of a vector of land-to-water delivery variables defined by vector \( Z_{iD_n} \), with a vector coefficient of \( \theta_D \). \( A' \) is the aquatic transport function applied to reach \( i \) and applies to base flow or total streamflow transport from the midpoint of reach \( i \) to the outlet of reach \( i \). Detailed descriptions of the theory and development of the SPARROW model are available from Smith et al. [1997] and Schwarz et al. [2006]. Details regarding the UCRB SPARROW network development and input data are provided in the supporting information.

### 2.2.2.1. Estimates of Base Flow Discharge to Streams

Regression-derived estimates of daily SC, measured daily stream discharge, and a conductivity mass balance approach were used to estimate long-term mean annual base flow for 146 (155 for mean annual streamflow) streams and rivers in the UCRB that represent the range of environmental watershed characteristics found in the Basin (Figure 1). Conductivity mass balance-derived base flow estimates represent the integration of many different groundwater flow paths, including deep regional groundwater and shallow near-stream flow paths [Miller et al., 2014; Rumsey et al., 2015]. Tillman and Anning [2014] applied load estimation methods [Schwarz et al., 2006] to measured discrete SC data and continuously measured discharge data collected between 1984 and 2012 to estimate daily SC at 320 sites in the UCRB. These regression-derived estimates of SC served as the initial data set from which the conductivity mass balance-derived estimates of mean annual base flow reported here were obtained. The SC and discharge data from 229 of these sites were identified as being suitable for estimation of base flow by Rumsey et al. [2015], who describe the requirements for data use, including screening for reservoir impacts, and the estimation of base flow using conductivity mass balance hydrograph separation. Data from 73 of the 229 sites were standardized to a base year of 2010 for discharge and SC, data from 82 sites were standardized to 2010 for discharge only, and data from 74 sites were not standardized for discharge or SC during the load estimation step due to sparse data availability near the base year. Standardization to a base year adjusts for among-site differences in data record lengths, sample sizes, and temporal variability in discharge. The long-term mean annual estimates of base flow or total streamflow generated from the standardized data represent the base flow or total streamflow that would occur in the base year under average hydrological conditions, reflecting both the conditions of nonflow factors in the base year and average hydrological conditions that prevailed in the base year [Schwarz et al., 2006], thereby providing a robust set of calibration data for use in the development of the SPARROW models. The 74 sites at which data were not standardized for discharge or SC were eliminated from the data set. All 73 sites with data standardized to a base year of 2010 for both SC and discharge were retained for base flow estimation, as were 73 of the 82 sites with data standardized to 2010 for discharge only (those sites that did not have temporal trends in SC following standardization for discharge, as identified using a Seasonal Kendall trend test [Hirsch et al., 1982], were retained). Discharge
data from all 155 sites with data standardized to 2010 for SC and discharge or discharge only were used for the mean annual streamflow model. The standardized SC and discharge data were used to estimate base flow at a daily time step for the period of record using conductivity mass balance hydrograph separation (see Rumsey et al. [2015] for details). Long-term mean annual base flow (or total streamflow for the mean annual streamflow model) was calculated as the mean of the annual standardized estimates at each site and used as calibration data for the SPARROW models. Mean annual base flow at the 146 calibration sites ranged from $1.8 \times 10^6$ to $3.1 \times 10^8$ m$^3$/yr, with a mean of $2.5 \times 10^8$ m$^3$/yr. The distribution of base flow estimates is shown in Figure S1 of the supporting information.

### 2.2.2. Source and Land-To-Water Delivery Variables

Conceptually, all base flow or streamflow originates as precipitation on the land surface. Therefore, precipitation values apportioned among different geologic groups were the only source variables that were assessed for inclusion in the model. In addition to precipitation, many different watershed characteristics influence base flow hydrology, including land use, soil characteristics, geomorphology, and climate [McGuire et al., 2005; Mwakalila et al., 2002; Ma et al., 2009; Tague and Grant, 2009; Price 2011; Price et al., 2011; Reynolds et al., 2015; Rumsey et al., 2015]. Several land-to-water delivery variables that have been identified previously as influencing base flow hydrology [Price, 2011] were tested for significance in the model, including percent land use, soil type, temperature, actual evapotranspiration (AET), percent snow cover, and topographic descriptors (slope, elevation, and topographic relief). A complete list of variables tested for inclusion in the model is provided in Table 1. The data sources for all source and land-to-water delivery variables that were tested for inclusion in the final model are described in the supporting information. Recent studies highlight the potential influence of anthropogenic activities on base flow recession [Wang and Cai, 2009; Thomas et al., 2013]. Therefore, variables such as urban and agricultural land use were used as surrogates for the potential influences of anthropogenic activities on base flow, and were tested as possible land-to-water delivery variables. In-stream transformation (loss) of base flow or total streamflow was estimated by the model as a function of mean reach travel time, and assuming first-order kinetics, such that the rate of loss of base flow or total streamflow is expressed as the fraction of base flow or total streamflow lost per unit travel time. Details of travel time estimation are provided in the supporting information. Reservoir attenuation, estimated as a function of areal hydraulic load in reservoirs, was also tested, but was not identified as a significant process, and was therefore not included in the final model. A nonparametric bootstrapping procedure with 200 iterations was used to define 90% confidence intervals for each model coefficient [Schwarz et al., 2006]. Only statistically significant model variables were retained for use in the final models.

### 2.2.3. In-Stream Transport

Both incremental and total mean annual base flows were estimated for each of the 10,789 reaches in the UCRB. Incremental base flow is the base flow generated within each reach and transported to the outlet of that reach (see second summation term in equation (1)). Total mean annual base flow is the incremental base flow plus accumulated base flow from all upstream reaches that is delivered to the outlet of the reach (i.e., Baseflowi, in equation (1)). Estimates of incremental and total mean annual base flow were used to estimate the fraction of base flow generated within a given reach that is delivered to (or lost during transport to) some downstream point. The fraction of base flow delivered from each reach to the Lower Colorado River Basin was estimated, as was the fraction delivered to the outlet of 58 watersheds defined by eight digit hydrologic unit codes (HUC8) [Seaber et al., 1987] (Figure 1d).

### 2.2.4. Model Fit and Statistical Analyses

Many different model configurations were tested prior to defining the final set of variables used in the models. Model fit was assessed using the overall model root-mean-square error (RMSE), $p$ values associated with statistical significance of model terms, and the coefficient of determination ($R^2$). Model fit was also assessed using the mean absolute error (MAE), mean absolute percentage error (MAPE), and mean percentage error (MPE) as measures of the magnitude of error in predictions. The overall model fit was assessed using the overall model root-mean-square error (RMSE), estimated as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

where $n$ is the number of observations, $y_i$ is the observed value, and $\hat{y}_i$ is the predicted value. Model fit was also assessed using the mean absolute error (MAE), estimated as:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$$

and the mean absolute percentage error (MAPE), estimated as:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\%$$

The coefficient of determination ($R^2$) was calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

where $\bar{y}$ is the mean of the observed values. Model fit was also assessed using the mean percentage error (MPE), estimated as:

$$MPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\%$$

Table 1. Land-To-Water Delivery Variables Tested for Potential Inclusion in the SPARROW Models

<table>
<thead>
<tr>
<th>Variables Tested</th>
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<tbody>
<tr>
<td>Physical Watershed Characteristics</td>
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<tr>
<td>Catchment slope</td>
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<tr>
<td>Mean elevation</td>
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<tr>
<td>Topographic relief</td>
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<tr>
<td>Land Use/Cover (%)</td>
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<td>Agriculture</td>
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<tr>
<td>Urban</td>
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<tr>
<td>Forest</td>
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<tr>
<td>Wetlands</td>
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<tr>
<td>Irrigated area</td>
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<tr>
<td>Soil Variables</td>
</tr>
<tr>
<td>Horizon thickness</td>
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<tr>
<td>Percent clay content</td>
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<tr>
<td>Percent silt content</td>
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<tr>
<td>Percent sand content</td>
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<tr>
<td>Permeability</td>
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<tr>
<td>Climatic Variables</td>
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<tr>
<td>Snow water equivalent</td>
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<tr>
<td>Percent snow cover</td>
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<tr>
<td>Temperature</td>
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<tr>
<td>Actual evapotranspiration</td>
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<tr>
<td>Potential evapotranspiration</td>
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*Details regarding data sources and processing are provided in the supporting information.*
individual model variables, multicollinearity among model variables, and residual plots. All statistics were generated based on comparisons between observed and predicted values in natural log units. All potential land-to-water delivery variables were transformed to approximate a normal distribution. Spatial autocorrelation among model residuals was assessed using Geary’s C statistic \cite{Geary, 1954}.

Multiple linear regression was used to identify potential drivers of in-stream loss of base flow. Total annual in-stream loss of base flow, between the time that the base flow first discharged to the stream environment and when it reached the outlet of the watershed, was calculated for each of 58 HUC8 watersheds in the UCRB. These 58 estimates of HUC8-scale in-stream base flow loss were used as the response variable in the regression model. Mean annual base flow generated (i.e., sum of incremental base flow), total estimated actual evapotranspiration (AET; see supporting information for details on AET data), estimates of irrigation withdrawal volumes, and estimated annual change in reservoir storage in each watershed were tested as explanatory variables. Natural logarithm transformations were applied to the mean annual base flow generated and AET to approximate normal distributions.

2.3. Graphical Hydrograph Separation Base Flow Index

Mean reach base flow index (ratio of base flow to total flow (percent)) data derived using a graphical hydrograph separation approach \cite{Wahl and Wahl, 1988, 1995} (hereafter BFI-graphical) were determined from a 1 km raster developed by Wolock \cite{2003}. The raster was developed by interpolating between BFI-graphical point values estimated at USGS streamgages. The point values were computed using an automated graphical hydrograph separation algorithm \cite{Wolock, 2003}. The BFI raster was resampled to 10 m cell size and a mean BFI-graphical value was calculated for each reach in the SPARROW network. BFI-graphical estimates were compared with BFI estimates obtained from the conductivity mass balance-based SPARROW model.

3. Results and Discussion

3.1. Model Assessment

Model statistics signify a good fit of the models to the calibration data (Table 2). Volume R^2 values indicate that the model explained 94% of the variability in mean annual base flow and 95% of the variability in mean annual streamflow. Yield R^2 values, which provide a more useful measure of model performance because they remove area-volume correlations, were 0.76 and 0.85 for the mean annual base flow and total streamflow models, respectively. RMSE values were 0.44 (base flow) and 0.38 (streamflow). Residuals were normally distributed as a function of the predicted mean annual yield of base flow (Figure 2a) and streamflow (Figure 2b). Spatially, both models slightly underpredicted volume at lower elevations and slightly overpredicted at higher elevations, and model precision was greater (smaller interquartile range) at lower elevations (Figures 2c and 2d). Geary’s C was 1.07 (p = 0.27) and 1.03 (p = 0.58) for the mean annual base flow and total streamflow models, respectively, indicating that there was not spatial autocorrelation in the residuals.

The same source variables, land-to-water delivery variable, and transformation processes identified as providing the best fit to the calibration data for the base flow model were also identified as providing the best fit to the total streamflow calibration data, and were therefore used for both models (Table 2). This finding is advantageous because developing separate SPARROW models with similar specifications and calibration sites allows for comparison among the model results \cite{Alexander et al., 2008}, including calculation of BFI values. The mean annual base flow and total streamflow models included precipitation on crystalline and volcanic rocks and precipitation on sedimentary rocks as the two sources of base flow (or streamflow) to streams, topographic relief as the single land-to-water delivery variable, and in-stream loss (Table 2). The model estimated coefficients associated with precipitation on crystalline and volcanic rocks were nearly identical to those estimated for precipitation on sedimentary rocks for both the base flow and streamflow models, with the coefficients for streamflow being greater than those for base flow by factors of 2. However, because sedimentary rocks are the dominant lithology in the UCRB, 92% of the estimated mean annual base flow and streamflow in the UCRB was estimated to be derived from precipitation on sedimentary rocks, with the remaining 8% from precipitation on crystalline and volcanic rocks. The source coefficients can be interpreted as the volume of base flow generated per unit precipitation, under the assumption that the spatially variable land-to-water delivery factor (topographic relief) is uniformly distributed at average conditions throughout the reach. The land-to-water delivery function \(D_t(Z^j, h^j)\), equation (1)) is applied to each source, thereby increasing (for greater topographic relief) or decreasing (for less topographic release) the model-estimated base flow.
Land use and soil type have been identified as being important predictors of base flow in studies of small to mid-sized watersheds [Mwakalila et al., 2002; Ma et al., 2009; Price, 2011], but were not identified as significant predictors of base flow in the UCRB. This does not indicate that land use, soil, and aquifer

<table>
<thead>
<tr>
<th>Table 2. SPARROW Model Coefficients and Model Statistics for Base Flow and Total Streamflow Models</th>
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<tr>
<td>Model Parameters</td>
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<tr>
<td><strong>Base Flow Model</strong> (N = 146; RMSE = 0.44; Volume R² = 0.94; Yield R² = 0.76)</td>
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<tr>
<td>Sources</td>
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<tr>
<td>Precipitation on crystalline and volcanic rocks</td>
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<td>Precipitation on sedimentary rocks</td>
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<td>Land-to-water delivery</td>
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<tr>
<td>Topographic relief</td>
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<tr>
<td>In-stream loss</td>
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<tr>
<td>k1 (Q ≤ 1 m³ s⁻¹ and Temperature ≤ 5°C)</td>
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<tr>
<td>k2 (Q ≤ 1 m³ s⁻¹ and Temperature &gt; 5°C)</td>
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<tr>
<td>k3 (1 m³ s⁻¹ &lt; Q ≤ 5 m³ s⁻¹ and Temperature &gt; 5°C)</td>
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<tr>
<td>k4 (Q &gt; 5 m³ s⁻¹ and Temperature &gt; 5°C)</td>
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<tr>
<td><strong>Streamflow Model</strong> (N = 155; RMSE = 0.38; Volume R² = 0.95; Yield R² = 0.85)</td>
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<td>Sources</td>
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<td>k2 (Q ≤ 1 m³ s⁻¹ and Temperature &gt; 5°C)</td>
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<td>k3 (1 m³ s⁻¹ &lt; Q ≤ 5 m³ s⁻¹ and Temperature &gt; 5°C)</td>
</tr>
<tr>
<td>k4 (Q &gt; 5 m³ s⁻¹ and Temperature &gt; 5°C)</td>
</tr>
</tbody>
</table>

Land use and soil type have been identified as being important predictors of base flow in studies of small to mid-sized watersheds [Mwakalila et al., 2002; Ma et al., 2009; Price, 2011], but were not identified as significant predictors of base flow in the UCRB. This does not indicate that land use, soil, and aquifer

Figure 2. Model diagnostic plots for (a and c) the base flow model and (b and d) the streamflow model.
characteristics are not important variables determining the amount or temporal variability in base flow in small watersheds within the UCRB, but that at the regional scale, precipitation is the dominant driver of spatial variability in base flow. The positive coefficients for topographic relief indicate increased delivery of mean annual base flow and streamflow in areas of greater relief. This is consistent with a previously identified positive relationship between base flow and topographic relief in a study of base flow across the contiguous United States [Santhi et al., 2008]. In contrast, it has been reported that there is a negative relationship between residence time and flow path gradient [McGuire et al., 2005]. Base flow discharge to streams in high-elevation watersheds in the UCRB, with shallow alluvial aquifers, likely includes shallow subsurface flow discharging to the stream [Frisbee et al., 2011] with lower residence times than the larger-scale, older groundwater discharge to streams at lower-elevation sites. While there is likely to be a smaller contribution of long residence time water to high-elevation streams than low-elevation streams, the definition of base flow as an integration of many subsurface flow paths, including shallow, near-stream, low residence time subsurface water discharging to high-elevation streams, contributes to the finding of greater base flow in high relief, high-elevation watersheds.

In-stream loss rates were estimated according to a discrete functional form defined by four different stream classifications based on annual discharge—obtained from local bias-corrected discharge estimates derived from Basin Characterization Model reach runoff (see supporting information for details)—and air temperature in each reach (Table 2). The rationale for these classifications is that evaporative losses are expected to be greatest in reaches with lower streamflow and higher air temperature. For both models, in-stream loss rates were greatest in reaches with low mean annual flow (≤ 1 m³/s) and high mean annual air temperature (> 5°C), followed by low mean annual flow and low mean annual air temperature (≤ 5°C). Reaches with intermediate (1–5 m³/s) and high (> 5 m³/s) flows and high air temperatures also had statistically

Figure 3. SPARROW model estimates of (a) mean annual base flow and (b) mean annual base flow yield in the UCRB.
significant, albeit lower, rates of in-stream loss. The model did not identify coefficients that were significantly different from zero for reaches with intermediate or high flows and low air temperatures, suggesting that temperature may be a more important driver of in-stream loss of base flow in the UCRB than streamflow. Further discussion of potential environmental drivers of in-stream loss of base flow is provided below.

3.2. Base Flow Discharge to Streams

Estimated mean annual base flow was generally greater at higher elevations, and accumulated during transport through the surface water network of the UCRB, with the greatest mean annual base flow in the large main stem rivers (Figure 3a). The estimated delivery of mean annual base flow from the UCRB to the Lower Colorado River Basin was $3.4 \times 10^9 \pm 1.8 \times 10^8 \text{ m}^3/\text{yr}$, which is 10% of the volume of Lake Mead at full capacity. Few independent estimates of base flow in the UCRB are available in the literature. However, an estimate of annual base flow at the outlet to the UCRB was obtained by calculating the mean discharge measured at the Colorado River at Lee’s Ferry (USGS gage 09380000) during low flow conditions (15 August to 15 March) for the years prior to the construction of Glen Canyon Dam (1922–1954). The mean low-flow time-period discharge prior to the construction of the Dam was $3.8 \times 10^9 \pm 1.2 \times 10^9 \text{ m}^3/\text{yr}$, which is similar to our estimated delivery of mean annual base flow from the UCRB to the Lower Colorado River Basin of $3.4 \times 10^9 \pm 1.8 \times 10^8 \text{ m}^3/\text{yr}$. Using long-term median August–March streamflow as an indicator of the groundwater contribution to the Colorado River, it has been estimated $2.2 \times 10^9 \text{ m}^3/\text{yr}$ of water is discharged from groundwater to streams in the watershed above the Colorado River at Cisco, UT (USGS gage 09180500) [Rosenberry, 2008]. This estimate is nearly identical to the SPARROW-derived estimate of mean annual base flow of $2.0 \times 10^9 \pm 9.9 \times 10^8 \text{ m}^3/\text{yr}$ at this site. Mean annual base flow yields for the 10,789 reaches averaged 48 mm/yr (interquartile range: 7.6–63 mm/yr), with greater yields generally observed at higher elevations (Figure 3b). Mean annual base flow yields at the outlets of the 58 HUC8 watersheds in the UCRB were positively correlated with the average elevations in the watersheds (Figure 4a; $R^2 = 0.70; p < 0.001$).

In contrast to the general patterns of greater mean annual base flow and yield at higher elevations, the fraction of total flow estimated to be base flow was generally lower at higher elevations in the UCRB (Figure 5a). The average BFI from the 10,789 reaches in the UCRB was 0.56 ± 0.13 (interquartile range: 0.46–0.63), indicating that on average, over half of the streamflow in the UCRB originated as base flow. Low BFI water (i.e., runoff) was routed through major rivers draining the eastern and southern Rocky Mountains (Colorado and San Juan Rivers; Figure 5a). At the outlet to the UCRB, it is estimated that 40% of the annual streamflow discharging to the Lower Colorado River Basin was base flow. Average BFI values at the outlets of the 58 HUC8 watersheds in the UCRB were negatively correlated with the average elevation in the watersheds (Figure 4b; $R^2 = 0.47; p < 0.001$). Taken together with the observed positive relationship between average elevation and base flow yield (Figure 4a), this finding suggests that while there is a greater contribution of base flow in watersheds at higher elevations, base flow is less important for sustaining mean annual streamflow (i.e., constituents a lower fraction of mean annual streamflow) in these areas relative to higher BFI watersheds at lower elevations.
The average of the conductivity mass balance-derived SPARROW BFI estimates from the 10,789 reaches in the UCRB (0.56 ± 0.13) was nearly identical to the average of the BFI-graphical estimates (0.58 ± 0.10; interquartile range: 0.52–0.65). The conductivity mass balance-derived SPARROW BFI values (Figure 5a) are estimated at a finer-scale spatial resolution than the BFI-graphical estimates (Figure 5b) because of differences in the approaches used to estimate BFI spatially. The SPARROW approach estimates BFI in each of 10,789 reaches as described above, and the BFI-graphical approach interpolates between point estimates of BFI made at streamgages [Wolock, 2003]. The BFI-graphical estimates were generally greater than the SPARROW BFI estimates at higher elevations (Figure 5b).

Figure 5. Estimated base flow index (BFI) values in the UCRB from (a) the conductivity mass balance-derived SPARROW estimates and (b) the graphical hydrograph separation approach of Wahl and Wahl [1988, 1995], as reported by Wolock [2003].

A comparison of the average conductivity mass balance-derived SPARROW BFI and BFI-graphical estimates in 58 HUC8 watersheds in the UCRB identifies an inverse relationship between the two estimates (Figure 6). This inverse relationship is due in part to the diversity of hydrologic conditions in the UCRB (see Figure 1) and the differences in how base flow is estimated by the two methods. Conductivity mass balance-derived SPARROW BFI values were generally greater than BFI-graphical values at sites with a low percent snow cover on 1 April, whereas the opposite was true for sites with a greater percent snow cover on 1 April (Figure 6). These finding are consistent with those of previous studies. Conductivity mass balance-derived BFI estimates have been shown to be greater than graphical-derived BFI estimates in nonsnowmelt dominated systems [Sanford et al., 2011], which are more hydrologically similar to lower-elevation HUC8 watersheds in the UCRB. In such systems, it has been suggested that the conductivity mass balance method estimates greater base flow than graphical approaches because the conductivity mass balance method predicts a greater component of preevent water during hydrograph peaks [Sanford et al., 2011]. Conversely, conductivity mass balance-derived BFI estimates have been shown to be less than BFI-graphical estimates in snowmelt-
dominated watersheds [Rumsey et al., 2015], and watersheds with a single extended high-flow season [Kronholm and Capel, 2015], similar to that of snowmelt-dominated systems. This is potentially due to the use of short (often 5 day) time periods for identifying minimum daily flow values for use in graphical hydrograph separation approaches, at snowmelt-dominated sites that have extended (30–90 day) periods of high flow [Miller et al., 2015]. Indeed, it has been suggested that graphical hydrograph separation approaches may be inappropriate for use in systems with hydrologic regimes other than those with short-duration storm events (e.g., snowmelt-dominated watersheds) [Wahl and Wahl, 1995; Santhi et al., 2008].

### 3.3. In-Stream Loss of Base Flow

The percentage of predicted mean annual base flow in the UCRB lost during in-stream transport to the Lower Colorado River Basin was estimated based on travel time and the model estimates of in-stream loss rates as a function of mean annual discharge and air temperature reported in Table 2. The estimated total incremental mean annual base flow (prior to in-stream loss) in the UCRB was $1.8 \times 10^{10} \pm 8.8 \times 10^9$ m$^3$/yr. Eighty-two percent ($1.5 \times 10^{10} \pm 8.8 \times 10^9$) of this base flow was lost during in-stream transport to the Lower Basin. The percentage of mean annual base flow generated in each incremental reach that was delivered to the Lower Colorado River Basin is shown in Figure 7. The percent base flow delivered to the Lower Basin increased with stream size and displayed a dendritic pattern (Figure 7). This pattern is driven largely by the shorter travel times in the large main stem rivers relative to the smaller headwater streams [Schwarz et al., 2006; Alexander et al., 2008].

In addition to the overall pattern of greater percent base flow delivered to the Lower Colorado River Basin with greater stream size, a greater fraction of base flow generated in higher-elevation watersheds is predicted to be transported to the Lower Basin relative to base flow generated in lower elevation, nonmain stem watersheds. For example, 26–50% of the mean annual base flow generated in the central and southern Colorado Rocky Mountains, Wind River Range, and Uinta Range is generally delivered to the Lower Basin, whereas less than 10% of the mean annual base flow generated in lower-elevation watersheds of the Colorado Plateau is generally delivered to the Lower Basin (Figure 7). This pattern is further demonstrated in a plot of the fraction of mean annual base flow generated in each of 58 UCRB HUC8 watersheds that is delivered to the outlet of those watersheds as a function of mean watershed elevation, which shows a statistically significant positive relationship (Figure 8; $R^2 = 0.58; p < 0.001$). Possible natural and anthropogenic processes contributing to this pattern include greater rates of evapotranspiration and greater amounts of water withdrawals for irrigation in the warmer, lower-elevation portions of the watershed.

Natural and anthropogenic processes contributing to the observed spatial patterns in predicted in-stream base flow loss were investigated with multiple linear regression analysis. Normal probability plots and plots of the model residuals versus predicted HUC8 base flow loss indicated that the assumptions of normality of the distribution and the independence and homoscedasticity of the model residuals were upheld. Multicollinearity among explanatory variables was not a problem, as indicated by variance inflation factors [Marquardt, 1970] that were less than 3 for all explanatory variables. There was
a good model fit using the explanatory variables tested ($R^2 = 0.76; p < 0.001$; Table 3). Of the explanatory variables investigated, watershed-scale mean annual incremental base flow generation, AET, and irrigation withdrawals were identified as statistically significant variables explaining the spatial variability in in-stream base flow loss (Table 3). Change in estimated reservoir storage was not identified as a significant predictor of in-stream base flow loss. Mean annual base flow generated in the watershed was significantly, but weakly ($p = 0.02$) correlated with in-stream base flow loss. AET and irrigation
withdrawals, both of which have been shown to influence the connected groundwater-surface water system [Winter et al., 1998; Price, 2011], were strong predictors of in-stream base flow loss \((p < 0.001)\). We are not able to differentiate between water lost to evapotranspiration from the in-stream environment versus that lost from the surrounding catchment. However, total AET in the Basin \((8.1 \times 10^{10} \text{ m}^3/\text{yr})\) is approximately 5 times greater than our estimates of base flow lost during in-stream transport \((1.5 \times 10^{10} \text{ m}^3/\text{yr})\), suggesting that evapotranspiration is likely a dominant driver of in-stream base flow loss. Another possible mechanism of in-stream base flow loss that would contribute to the net model estimates of in-stream loss, but that was not explicitly investigated here is focused recharge to aquifers [Healy, 2010], which may account for some of the unexplained variation in in-stream base flow loss.

### 3.4. Conclusions and Implications

One challenge to developing dynamic mechanistic base flow models in large watersheds is the extensive infrastructure and data required to support such models. We used a simple, empirical watershed modeling tool, SPARROW, to present the first spatially distributed regional estimates of base flow developed from conductivity mass balance hydrograph separation. Results were interpreted to provide insight into spatial variability in long-term mean annual base flow conditions at the spatial scale of the UCRB \((2.8 \times 10^5 \text{ km}^2)\).

The conductivity mass balance approach for generating the base flow estimates used as model calibration data provides a direct relation between estimated base flow and physical and chemical processes and flow paths in the basin. Results suggest that, at the spatial scale of the UCRB, precipitation is the dominant driver of spatial variability in base flow, and that base flow is critical for sustaining surface water flow in the Basin. On average, 56% of the surface water in the UCRB is estimated to have originated as base flow, and much of this water originated in high-elevation drainages. The spatially distributed estimates of mean annual base flow indicate that the amount of base flow in low-elevation arid portions of the watershed is less relative to higher-elevation portions of the UCRB. This is consistent with the finding of negligible changes in loads (largely a function of negligible changes in discharge) from groundwater and small tributaries along a \(\sim 200 \text{ km} \) stretch of the Colorado River in eastern Utah [Shope and Gerner, 2014]. Despite the simplicity of the approach, the resulting base flow estimates are consistent with those reported previously, and spatial variability in predicted in-stream base flow loss can be explained largely by evaporative loss and water withdrawals for irrigation.

Ongoing anthropogenic activities such as groundwater pumping are likely to influence base flow conditions in the UCRB. It has been estimated that groundwater storage in the UCRB declined at a rate of \(1.7 \times 10^9 \text{ m}^3/\text{yr}\) from 2004 to 2014 [Castle et al., 2014] during an extended drought period, and \(2.6 \times 10^8 \text{ m}^3/\text{yr}\) from May 2011–March 2013 [Scanlon et al., 2015], which included both wet and dry periods. These declines are equivalent to 9% and 1%, respectively, of our estimated mean annual base flow discharge to streams in the UCRB, and have been attributed to both wet and dry climate cycles as well as groundwater pumping, which is expected to increase in the future. A continued decline at this rate coupled with our estimate that

![Diagram](Figure 8. Estimated percentage of base flow generated in each of 58 HUC8 watersheds in the UCRB that is delivered to the outlet of those watersheds as a function of mean watershed elevation.)

<table>
<thead>
<tr>
<th>Table 3. Multiple Linear Regression Results for Estimated HUC8 Base Flow Loss as a Function of Mean Annual Base Flow Generated in the HUC, Actual Evapotranspiration (AET), Irrigation Withdrawals, and Change in Reservoir Storage</th>
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<tbody>
<tr>
<td><strong>In Base Flow Generated (km³/yr)</strong></td>
</tr>
<tr>
<td>Intercept</td>
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<td>Coefficient</td>
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<tr>
<td>Standard Error</td>
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<td>( N = 58, \text{ Residual Standard Error } = 0.06, R^2 = 0.76 )</td>
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82% of the base flow that discharges to streams in the UCRB is lost during in-stream transport to the Lower Colorado River Basin will act to further reduce the volume of surface water that is delivered to the Lower Basin.

Given the dependence on base flow for sustaining surface flows and anthropogenic use of those flows, there is an urgent need for continued development of predictive models that represent complex coupled human-natural systems to better quantify current base flow conditions and response to future change. The results presented here provide a first approximation of present-day base flow conditions at the regional scale based on conductivity mass balance estimates of base flow. These estimates may serve as a foundation for future studies that predict base flow response to climate and anthropogenic change. Coupling this approach with process-based models that quantify fine-scale temporally dynamic watershed processes that influence base flow discharge to streams will further our ability to address regional to global-scale water management challenges [Gorelick and Zheng, 2015] in both the UCRB and other watersheds throughout the world.

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References
Eckhardt, K. (2008), A comparison of baseflow indices, which were calculated with seven different baseflow separation methods, J. Hydrol., 352, 168–173, doi:10.1016/j.jhydrol.2008.01.005.


