

Review

A Review of Current Capabilities and Science Gaps in Water Supply Data, Modeling, and Trends for Water Availability Assessments in the Upper Colorado River Basin

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Abstract: The Colorado River is a critical water resource in the southwestern United States, supplying drinking water for 40 million people in the region and water for irrigation of 2.2 million hectares of land. Extended drought in the Upper Colorado River Basin (UCOL) and the prospect of a warmer climate in the future pose water availability challenges for those charged with managing the river. Limited water availability in the future also may negatively affect aquatic ecosystems and wildlife that depend upon them. Water availability components of special importance in the UCOL include streamflow, salinity in groundwater and surface water, groundwater levels and storage, and the role of snow in the UCOL water cycle. This manuscript provides a review of current “state of the science” for these UCOL water availability components with a focus on identifying gaps in data, modeling, and trends in the basin. Trends provide context for evaluations of current conditions and motivation for further investigation and modeling, models allow for investigation of processes and projections of future water availability, and data support both efforts. Information summarized in this manuscript will be valuable in planning integrated assessments of water availability in the UCOL.

Keywords: Colorado River; drought; water availability; hydrology; snow; water quality

1. Introduction

The Colorado River (Figure 1) is an important water resource in the southwestern United States (U.S.), supplying drinking water for 40 million people in the U.S. and Mexico and water for irrigation of 2.2 million hectares (5.5 million acres) of land [1]. The Colorado River and its tributaries are an essential source of water for at least 22 federally recognized tribes, 7 National Wildlife Refuges, 4 National Recreation Areas, and 11 National Parks [1]. In 2019, the U.S. Geological Survey (USGS) Water Resources Mission Area (WMA) initiated planning efforts for a number of USGS programs to conduct science activities in the Upper Colorado River Basin (UCOL; Figure 2) to improve understanding of hydrologic processes, investigate processes affecting water quality, improve capabilities to estimate water use, and develop innovative methods and approaches to project future water availability for water managers in the basin. The UCOL Integrated Water Availability Assessment (IWAA) project was created to assess water availability in the basin. Evaluating water availability involves assessing the ability to access a required amount of water of sufficient quality for a given purpose. The UCOL water availability assessments evaluate water quantity and quality in both surface and groundwater, as related to human and ecosystem needs, and as affected by human and natural influences. While the availability of water is dependent

on several integrated components describing the supply, quality, and use of water, this manuscript focuses on UCOL water supply and the important water quality issue of salinity, and does not address water use.



Figure 1. The Colorado River Basin in the southwestern United States and northern Mexico.

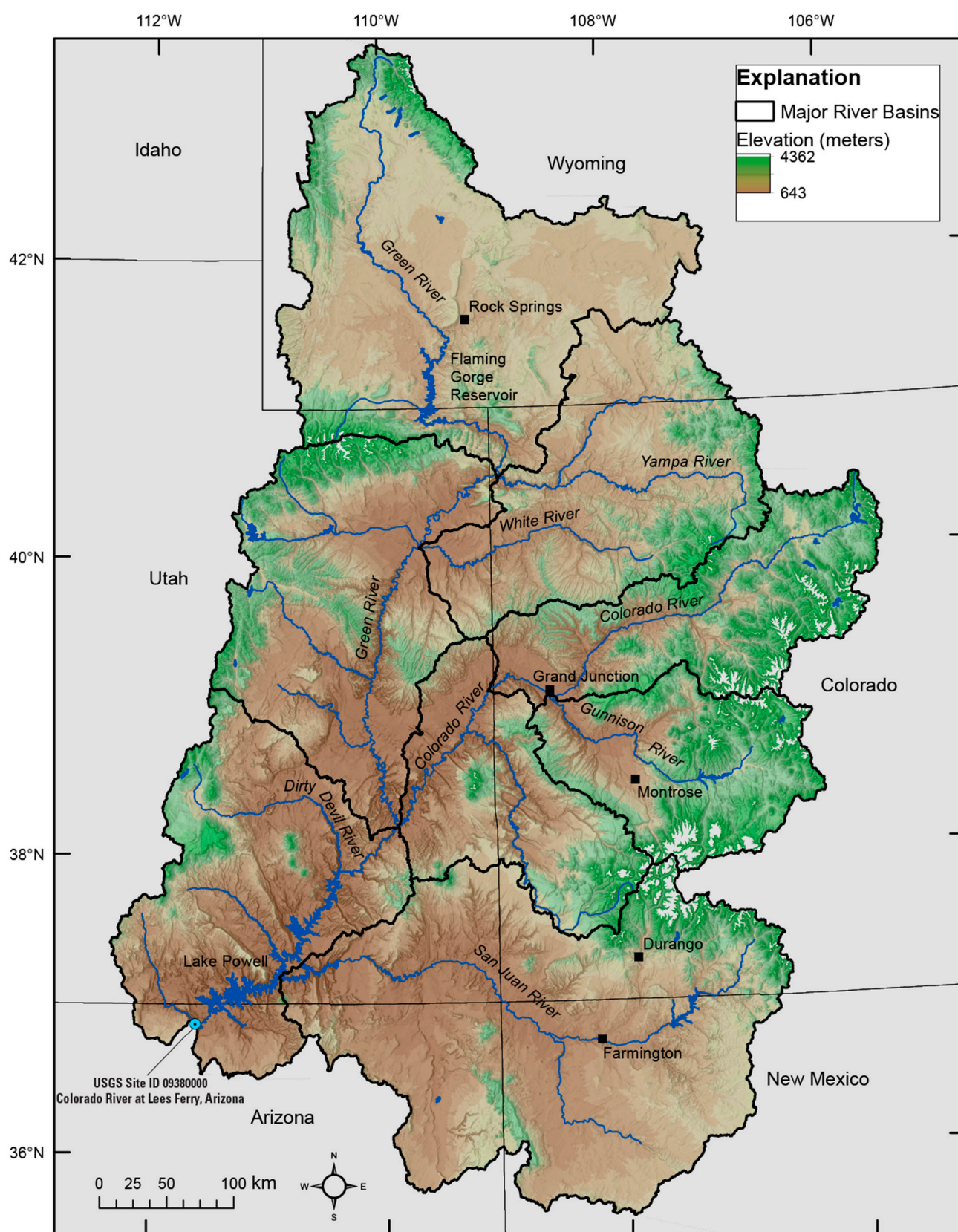


Figure 2. Map of the Upper Colorado River Basin showing major tributaries and sub-basins.

As discussed in more detail in Background Section 2, water availability components of special importance (priority components) in the UCOL include streamflow, salinity in groundwater and surface water, groundwater levels and storage, and the role of snow in the UCOL water cycle. In addition to providing background information on UCOL hydrology, water quality, and water use issues, this manuscript details a summary of current “state of the science” for each of these UCOL priority water availability components with a focus on identifying gaps in data, modeling, and trends in the basin. Trends provide context for evaluations of current conditions and motivation for further investigation and modeling, models allow for investigation of processes and projections of future water availability, and data support both efforts. Understanding gaps in current data and capabilities in trends assessments and modeling in the basin is vital for planning science activities for integrated assessments of water availability in the UCOL.

2. Background

From headwaters in the Rocky Mountains, the Colorado River flows more than 2300 km through seven U.S. states and Mexico to discharge into the Gulf of California. The Colorado River and its tributaries drain an area of 640,000 km² in parts of the U.S. states of Wyoming, Utah, Colorado, New Mexico, Arizona, Nevada, and California and the Mexican states of Sonora and Baja California. The Colorado River Compact of 1922 [2] (the Compact) divided the Colorado River into upper and lower basins at the compact point of Lee Ferry, Arizona, a location on the River about 0.6 km downstream from the mouth of the Paria River and about 1.4 km downstream from USGS stream-gage 09380000 “Colorado River at Lees Ferry, AZ” [3]. About 90% of the flow in the lower Colorado River at Lake Mead originates in the upper basin [4]. The Compact divides water in the River equally between the upper and lower basin states, with each basin allotted 9.25 km³ (7.5 million acre-feet) per year, and requires upper basin states to deliver an aggregate of 92.5 km³ (75 million acre-feet) over any ten consecutive water years to Lee Ferry [2]. Additionally, a 1944 treaty guarantees that 1.8 km³ (1.5 million acre-feet) per year of Colorado River water be delivered to Mexico [5]. The River was apportioned based on hydrologic data that indicated Colorado River flow at Lee Ferry to be about 22.2 km³ (18.0 million acre-feet) per year [1]. It is now known that streamflow data used to apportion the River in the early 20th century were collected during an unusually wet period in the upper basin [6] and, thus, more historically normal flow conditions may not produce sufficient water for all apportioned uses. The Bureau of Reclamation (Reclamation) manages reservoirs in the upper and lower basins that total about 74 km³ of storage, about four times the average annual flow from the upper basin, to buffer against hydrologic variability and drought [1]. On 16 August 2021, Reclamation announced the 2022 operating conditions for Lake Powell and Lake Mead, with projections including the first ever Lake Mead Level 1 shortage condition in history [7]. This declaration resulted in 0.76 km³ less water available for Arizona, Nevada, and Mexico [8]. Continuing drought in 2022 resulted in projected shortage reductions and water savings contribution of another 0.88 km³ from Arizona, Nevada, and Mexico in 2023 [9]. Extended drought in the basin and the prospect of a warmer climate in the future pose challenges for water managers to deliver on compact and treaty promises. Limited water availability in the future also will continue to negatively affect aquatic ecosystems and wildlife that depend upon them. Advancing scientific understanding and predictive capabilities of water availability in the upper basin is essential in order to provide assessments of water availability relevant to a range of water users from water managers to the general public.

UCOL Hydrology, Water Quality, and Water Use

The Colorado River that flows into Lake Powell at the pour point of the UCOL comprises three major tributaries: the Green River which begins in southern Wyoming, flowing southerly and incorporating tributary flow from the Yampa and White Rivers; the Colorado River which begins in high elevation areas of the Rocky Mountains in Colorado and flows southwesterly, incorporating the Gunnison and Dolores Rivers; and the San

Juan River which drains parts of southern Colorado and northwestern New Mexico and flows westerly (Figure 2). Mountain snowpack and snowmelt play a critical role in the hydrology of the UCOL, and thus the flow in the Colorado River. High elevation areas in the upper basin receive most of the precipitation and are cold enough to allow the accumulation of seasonal snowpack [10]. These limited areas produce a large portion of the runoff to streams in the basin—about 15% of the surface area of the basin contributes about 85% of the average annual runoff [10]. Runoff efficiency, defined as the ratio of runoff to precipitation, is estimated at 16% for the upper basin [10]. Owing to the limited area contributing a majority of basin runoff, changes in precipitation (both amount and timing) and temperature in these relatively small areas have a profound effect on resulting streamflow in the upper basin and subsequent reservoir storage throughout the basin.

The importance of groundwater contributions to the quantity and quality of streamflow in the UCOL has been gaining increased attention in the last decade [11–15]. On average, baseflow discharge constitutes 56% of water in streams in the UCOL [12] and it is estimated that 89% of dissolved solids loads in the UCOL originate from baseflow [13]. Declines in groundwater levels by relatively small amounts, resulting from reduced recharge or increased withdrawals, may turn a gaining stream reach into a losing one, which in turn can change dissolved solids concentrations in the stream. Because groundwater and surface water are a single resource [16], future management practices involving conjunctive use of groundwater and surface water may be required to maximize available water in the basin.

An important water-quality issue in the UCOL is elevated dissolved solids (salinity) concentrations in streams and rivers. The UCOL is the source of most of the $>7 \times 10^6$ metric tons of dissolved solids that flow annually past Hoover Dam [17]. Natural and anthropogenic sources contribute salinity to the Colorado River [18–20]. Natural sources, including geologic sources (sedimentary rocks) and saline springs, contribute about 68% of the salinity load to the River with the remaining 32% contributed by irrigated agricultural land [20]. High salinity levels in the Colorado River cause damages estimated at greater than \$300 million annually, mostly from corrosion and reduced agricultural yields [21]. Additionally, by treaty and subsequent agreements, the U.S. must deliver to Mexico 1.850 km^3 (1.5 million acre-feet) per year of Colorado River water that is, on an annual average, no more saline than 115 parts-per-million (ppm) higher than the salinity of water behind Imperial Dam (30 km from the U.S.-Mexico international boundary), plus or minus 30 ppm [5,22]. Cyclical oscillations in salinity that originate in the UCOL complicate Reclamation's ability to manage salinity in the river for delivery of water to Mexico [23].

How, and from where, water is used can have important impacts on the availability of water in a basin. Water use in the UCOL is primarily from surface water bodies (streams and reservoirs), with surface withdrawals accounting for 98% of water use in the basin from 1985 to 2010 [24]. If already allocated surface water supplies diminish under projected climate change, increased dependency on groundwater supplies may create negative feedback in the hydrologic system, with increased pumping reducing baseflow to streams, further decreasing streamflow. Although the largest category of water use in the UCOL is hydroelectric power generation (59% of total), little of this water is “consumptively used” and instead flows through power generation equipment and continues downstream (some consumptive use by hydroelectric power is attributed to reservoir evaporation) [24]. Agricultural irrigation accounts for the largest amount of withdrawals for off-stream use in the basin (80–90%), with public-supply withdrawals a distant second at 6–13% [24].

3. Review of Current UCOL Data, Modeling, and Trend Capabilities

A retrospective analysis of available data, modeling capabilities, and trends assessments in the UCOL was conducted in order to evaluate existing efforts that may be useful for UCOL water availability investigations and to identify gaps in current capabilities that could be addressed for future efforts. This state-of-the-science summary is not an exhaustive catalog of all data, modeling, and trends work done in the UCOL, but a description of

current science that may provide a foundation for improved water availability assessments. This review covers water availability components of special importance in the UCOL including streamflow, salinity in groundwater and surface water, groundwater levels and storage, and snow. Each water availability component discussion includes background information on why the component is important in the basin, a summary of findings from the data assessment relevant to the component and gaps in current data, a discussion of current models addressing the component and gaps in modeling capacity, and a discussion of available trends assessments of the component with gaps highlighted.

3.1. Streamflow

Streamflow is the primary water source for water users in the Colorado River Basin. Studies indicating the likelihood of declining streamflow in the UCOL as a result of climate change, combined with increasing population in the region that depends on the River for water supply, highlight the importance of projecting future availability of UCOL streamflow. Streamflow integrates climatic, hydrologic, and water-use drivers. Important climate-related drivers of streamflow include precipitation as rain and snow, temperature as it affects the accumulation and melting of snowpack, and temperature through evapotranspiration. Hydrologic processes that influence streamflow include runoff, infiltration, and groundwater discharge to, and recharge from, streams. Diversion of streamflow, storage and releases from reservoirs, and groundwater withdrawals that affect groundwater-surface-water interactions are water-use activities that affect streamflow.

3.1.1. Data

The data discovery effort for the UCOL was limited to continuous (time-series) streamflow measurements, as opposed to discrete measurements. This was because continuous measurements, usually taken at 15-min or 30-min intervals, provide more accurate estimates of the mean daily flow values typically used in water availability assessments.

Data from currently active or inactive streamflow gages at 1265 sites in the UCOL were identified, with the majority of gages (1108) operated by the USGS. As a result, most of the streamflow data for the UCOL has been collected by the USGS and is available from the National Water Information System (NWIS) Surface-Water Data web page [25]. The USGS is in the process, however, of replacing NWIS with a new system for the public to access water data called the Next Generation Monitoring Location Pages [26]. Real-time USGS streamflow data also will continue to be available from the National Water Dashboard [27]. The Colorado Division of Water Resources (CO DWR) [28], the Wyoming State Engineer's Office [29], and Northern Water [30] (which provides water to >1 million residents in northeastern Colorado) maintain their own streamflow gaging networks separate from the USGS, and the Bureau of Reclamation [31] measures releases from its reservoirs. These streamflow and reservoir release data are available from the public web pages maintained by those agencies. The U.S. Department of Energy [32] also has collected streamflow data at a small network of gages in the East River watershed as part of a research project improving understanding of hydrology in mountainous catchments, and these data are publicly available as well.

An initial review of available streamflow data did not indicate the existence of substantial temporal data gaps but identified some site redundancy and spatial data gaps. Thirteen percent of the gages have records greater than 50 years (with some records extending as far back to at least 1900), 23% have records between 10 and 25 years, 16% have records between 25 and 50 years, and 48% have records less than 10 years. There are instances where two agencies operate active gages that are co-located or close to one another on the same stream. As a result, the agencies are publishing two different (but very similar) sets of streamflow data, which may be confusing to people using the data. Additionally, the locations of the identified UCOL gages are overly representative of mid and large-sized streams while poorly representative of small, headwater streams (Table 1).

Table 1. Size distribution for stream reaches in the Upper Colorado River Basin.

Stream Order ¹	Percentage of Reaches	
	Gaged Reaches	All Reaches
1	9.2	48.8
2	19.2	21.7
3	26.9	12.1
4	23.9	6.9
5	12.3	4.1
6	6.0	3.7
7	1.5	1.9
8	0.9	0.9

Note: ¹ A ranking of the relative sizes of streams within a watershed, with the smallest unbranched tributary called first order, the stream receiving the tributary called second order, etc. [33].

3.1.2. Modeling Capabilities

Streamflow has the largest existing modeling capacity of the priority water availability components at the basin scale. Multiple U.S. agencies have developed streamflow forecasting models that make a range of forecasts throughout the UCOL at near-, mid-, and long-term timeframes and several national scale models include the UCOL. The National Oceanic and Atmospheric Administration's (NOAA) National Water Model (NWM) is one configuration of the Weather Research and Forecasting Hydrologic model (WRF-Hydro) that simulates streamflow and floods across the continental United States (CONUS) at hourly to 30-day time horizons. In addition to streamflow, the NWM provides a range of soil, snow, radiation budget, and groundwater outputs, and is intended to become the operational model for National Weather Service River Forecasting Centers in the future [10]. The USGS National Hydrologic Model (NHM) [34], using the Precipitation-Runoff Modeling System (PRMS) [35,36], is a model infrastructure for nationally consistent daily simulations of watershed processes that can be used to simulate and assess the effects of various combinations of climate and land use on watershed response. SUMMA and mizuRoute, developed at the National Center for Atmospheric Research (NCAR), provide a unified approach for process-based hydrologic modeling of water and energy budgets in the atmosphere above vegetation canopy to the river channel [37]. The SUMMA and mizuRoute modeling framework allow for testing of watershed modeling approaches, with applications for short-term to seasonal streamflow predictions to long range climate impact analyses. A standalone model of North America has been developed that could be used to initiate smaller area simulations [38]. A 50-year 3-h timestep retrospective simulation of the Western U.S. (HUC 12 spatial scale) has been completed [39].

ParFlow, a physically based, distributed, three-dimensional, integrated groundwater-surface water model that simulates water and energy fluxes through surface and subsurface systems simultaneously, has been applied at both the near-CONUS and UCOL scale to evaluate groundwater-surface water interactions [40–43]. ParFlow takes advantage of massively parallel, high-performance computing to support simulations of complex processes at 1 km resolution. At the UCOL scale, ParFlow was coupled with the Community Land Model (CLM), which added capabilities to represent many critical landscape processes including vegetation composition, surface energy budgets, snow hydrology, lakes, dust deposition, carbon and nitrogen cycling, dynamic land cover change, and land management [44,45].

A USGS GSFLOW model of the basin for 1980–2022 that couples a MODFLOW-2005 groundwater flow model on a monthly time step with a PRMS surface water model on a daily time step [46] could support improved understanding of the relationship between groundwater and surface water in the UCOL, investigate how that relationship has changed, and project how it may change in the future as a result of human use of water and climate change.

The USGS has several model codes that have been applied to predict streamflow throughout the basin including the Monthly Water Balance Model (MWBm), the Basin

Characterization Model (BCM), and Spatially Referenced Regressions on Watershed attributes (SPARROW) models. The MWBM estimates water balance components of the hydrologic cycle on a monthly time step and has been used to quantify water budgets and explore runoff response to climate change in the UCOL [47,48]. The MWBM has also been modified to improve representation of snow hydrology and runoff specifically in the UCOL [49]. The BCM is a regional water balance model that was developed to evaluate hydrologic differences among basins in the Desert Southwest and the hydrologic response to current and future climate scenarios. The BCM model has recently been updated and used in the UCOL to focus on drought, wildfires, and snowpack [50]. Spatially Referenced Regressions on Watershed attributes (SPARROW) is a spatially explicit hybrid process-based and statistical model that estimates water quality constituent loads in streams by linking monitoring data with information on watershed characteristics and load sources, routed through a stream network [51]. SPARROW streamflow and baseflow models [12,52] that include the UCOL have been developed and applied to quantify streamflow and baseflow response to future climate change [15,53].

The U.S. Bureau of Reclamation uses the Variable Infiltration Capacity (VIC) model [54] as well as several operations models to simulate the Colorado River system in RiverWare software. VIC is a macroscale semi-distributed hydrologic research model that solves the full water and energy balance at each model grid cell. VIC has been widely used in several influential studies of streamflow sensitivity and climate change projections in the UCOL [55,56] including the Bureau of Reclamation Colorado River Basin Water Supply and Demand Study [1].

Operational reservoir simulations in the UCOL are primarily done by Reclamation using their Colorado River Mid-Range Modeling System (CRMMS) and Colorado River Simulation System (CRSS) models, which are implemented in RiverWare software. The models simulate operations of the major Colorado River reservoirs and provide forecasts of the system on a monthly basis, including the volume of water in storage, reservoir elevations, dam releases, energy generation, streamflow and diversions to and from water users throughout the system. CRMMS is a basin-wide probabilistic model that evaluates future system conditions up to five years in the future and simulates monthly reservoir operations at nine UCOL reservoirs [57,58]. Ensemble Streamflow Prediction (ESP) natural streamflow estimates generated by the Colorado Basin River Forecast Center (CBRFC, described below) are used as the official unregulated inflow forecasts by Reclamation in CRMMS to produce mid-term operational projections. CRMMS is used to produce two important types of projections for the UCOL: the 24-month study projections and the 2-year probabilistic projections, that are used by Reclamation for planning reservoir operations. CRSS is a long-term policy planning model for monthly analysis of operations beyond two years. The model simulates long-term natural flow for 29 points in the CRB, as well as reservoir releases, water surface elevations, hydropower generation, and consumptive uses. CRMMS uses unregulated inflows (the flow that would be observed if there were no upstream reservoirs) for forecast points in the UCOL, while CRSS uses natural flows (flow measured at a streamgage without the effects of reservoir operations and diversions).

Several agencies provide operational streamflow forecasting at points in the basin. NOAA National Weather Service (NWS) CBRFC has several critical operational streamflow models within the Community Hydrologic Prediction System (CHPS) that provide sub-daily to seasonal water supply forecasts at locations throughout the basin. Central to CHPS are the Sacramento Soil Moisture Accounting (SAC-SMA, [59]) and SNOW-17 [60] models that serve as the primary hydrologic models used by the CBRFC. SNOW-17 is a temperature-index model that simulates snow accumulation and ablation. SAC-SMA is a lumped conceptual model that takes output from SNOW-17 and simulates soil moisture and runoff process that may become streamflow. This combination of highly calibrated models (SAC-SMA and SNOW-17) currently produces the best performance in simulating streamflow down to sub-daily time steps despite concerns that their forecast skill may decrease under conditions of climate and land cover change [10]. Seasonal and longer

forecasts are produced using ESP techniques, which apply historical weather temperature and precipitation sequences (1981–2010) to the model to create an ensemble of 30 streamflow forecasts (one per year of historical data used). Seasonal forecasts produced using Statistical Water Supply (SWS) methods based on principal component regressions are used for internal comparison to publicly released ESP results. CBRFC streamflow forecasts are used by Reclamation for reservoir operations planning.

The U.S. Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) uses their Visual Interactive Prediction and Estimation Routines (VIPER) [61] and newer Multi-Method Machine Learning Metasystem (M4) models [62,63] to forecast seasonal water supply at locations throughout the UCOL. The M4 system is a unique example of integrating next generation forecasting science, including machine learning, into operations to improve forecast accuracy and was guided by forecaster needs.

Water use and management, including reservoirs and diversions, have been included in a limited number of hydrologic models at small spatial scales. A Water Evaluation and Planning (WEAP) model of the Upper Colorado River Basin HUC 140100 has been developed to support water management decision making in the area [64]. The model simulates diversion from the basin to the Colorado Front Range and the response of the system, including reservoir storage, to drought-response measures under a changing climate. This model also has been used to test streamflow simulation sensitivity to incorporating multiyear temperature predictions [65].

Watershed Analysis Risk Management Framework (WARMF) is a tool designed to support watershed management decision making through watershed analysis studies and total maximum daily load (TMDL) calculations [66]. WARMF includes a hydrology and water-quality model that includes reservoir capabilities and stream diversions. Reservoirs can be simulated using either a one-dimensional vertically stratified approach or a two-dimensional approach using CE-QUAL-W2, and information about reservoir operations can be included [66]. Kopytkovskiy et al. [67] applied climate change projections to a WARMF model of the Upper Colorado and Gunnison River basins, including reservoirs and thousands of diversions, to analyze potential changes in precipitation, temperature, streamflow, and reservoir storage in response to future climate change.

Within the UCOL, a variety of machine learning techniques have been successfully applied to improve streamflow forecasting. One approach uses artificial neural networks (ANNs), which learn functions that relate input and output data from the input data (in contrast to process based models where the relationships between inputs and outputs are encoded based on expert knowledge of physical laws). Long short-term memory (LSTMs) networks are perhaps the most popular and widely used ANN with temporal memory [68]. LSTMs that can perform better than SAC-SMA (used by the National Weather Service River Forecast Centers in their ESP forecasts), the NWM, and PRMS [69–72] have been developed for locations across the country including the UCOL. Several LSTM networks (including Bayesian LSTM and physics-informed hybrid LSTM) have been developed for the East River watershed (within the UCOL) to investigate predictive capabilities in data-scarce regions and to compare with PRMS results [71]. Zhao et al. [73] developed long-lead seasonal streamflow prediction for 20 sites across the UCOL using stepwise linear regression and neural network forecast models.

Support vector machine models have been developed for three sites in the UCOL (Cisco, Green River, and Lee's Ferry) and along the Gunnison and San Juan River Basins. These models predict streamflow using oceanic-atmospheric oscillations with one and three-year lead times [74,75]. Random forest (RF) models developed to improve decadal streamflow forecasts at Lees Ferry, Arizona, using decadal temperature projections outperformed ESP and climatology in a 1982–2017 hindcast, and subsequent reservoir pool elevation projections (derived from Colorado River Mid-Range Modeling System driven by RF-generated streamflow projections) were improved [76]. Although application of machine learning techniques is relatively new and has not been widespread, results are promising for improved streamflow prediction accuracy. Machine learning methods can

provide improved models and predictive abilities (e.g., see [70,77]) relative to process-based models, but suffer from a lack of interpretability and explainability [68,78]. Their ability to predict under conditions not yet observed or of non-stationarity (such as climate change) is a subject of ongoing research and debate [79].

3.1.3. Trends

Numerous studies have quantified trends in streamflow across various time periods, both inter- and intra-annually and across various spatial scales over the past 30 years. Accurate estimates of future water availability rely on understanding recorded trends; therefore, many studies focus on identifying the sensitivity of streamflow to changes in climatic variables, thus, reference gages or those with naturalized streamflows are often used. Reference gages, such as those identified in the USGS Geospatial Attributes of Gages for Evaluating Streamflow version II database (GAGESII) [80], are sites with a relatively long period of record and minimal influence from trans-mountain diversions, reservoirs, and other anthropogenic factors. The most used naturalized streamflows are those calculated at 20 stream gages in the UCOL by the U.S. Bureau of Reclamation [6]. These streamgages represent distinct subbasins in the UCOL, have long periods of record (>100 years), and are associated with multiple climate networks. Additional data sets of naturalized streamflows exist [81] and could be used to quantify natural and anthropogenic processes contributing to streamflow depletion and augmentation. Observed streamflows from non-reference streamgages are also used in trend assessments when the influence of land cover, water use, and other anthropogenic change on streamflow is of interest. Very few studies were found that assessed streamflow trends on individual subbasins or tributaries of the UCOL (but see [82]).

Because snowmelt is the primary source of annual runoff in the UCOL, trends in metrics related to this late-spring peak in the annual hydrograph have received a lot of attention including investigations of timing of peak streamflow, center timing of streamflow, and runoff efficiency (ratio of streamflow to precipitation). Other streamflow statistics including percentiles, annual, minimums, and maximums are evaluated on annual, seasonal, and monthly timescales. Very little study has been done on low streamflow conditions in the UCOL, despite demonstrated linkages between snowpack and low streamflows in other western basins, including catchments in the Sierra Nevadas, California [83]. Given the importance of summer streamflows in moderating water demand for agriculture and urban outdoor use and ecological flows, hydrologic metrics representing timing, variability, and duration of mean- and low-flow conditions could be explored in greater detail.

Different trend techniques have been used to assess the magnitude and statistical significance of trends in streamflow. The most frequently used methods to assess monotonic trends are the non-parametric Mann-Kendall trend test and parametric linear regression. Parametric methods, such as linear regression and *t*-tests, require that data follow a normal distribution and are more powerful for normally distributed datasets [84]. Non-parametric methods, such as the Mann-Kendall test for trend and the seasonal Kendall trend test, do not require that data follow a normal distribution and are more powerful for non-normally distributed datasets [84]. Trends are assessed on annual, seasonal, and monthly timescales. Generally, trends are assessed between fixed starting and ending dates, though locally estimated scatterplot smoothing (LOESS) curves can be applied to better understand trends that vary over time (non-monotonic) [85]. Step changes within time series data, related to reservoir construction and climate events, were assessed using a non-parametric rank-sum test and parametric student's *t*-test [86,87]. Relationships among streamflow, temperature, and precipitation in the basin have been investigated using the concepts of temperature sensitivity and precipitation elasticity, estimates of the percent or fractional change in annual streamflow per percent or fraction change in temperature or precipitation [85]. The data used in these estimates have been determined empirically or through water balance model simulations. Differences in results, such as the relative influence of temperature and

precipitation on streamflow, can result from differences in the spatiotemporal scale of input data and differences in water balance model inputs and assumptions.

Nearly all studies included in this review found decreases in one or more metrics of streamflow since the early 1900s to the early 2000s. Shifts to earlier runoff timing associated with decreases in spring snowpack were found in many parts of the UCOL [88,89], as well as decreases in annual streamflow at Lees Ferry [90]. Sub-annual assessments show increases in streamflow during winter months and decreases during the traditional peak runoff season through summer [86,89,91]. There is a consensus from recent studies that around half or more of the declining streamflow trend at Lees Ferry is due to variability and trends in precipitation [90,92–94]. It is also clear that warming temperatures can play a long-term role in streamflow reductions, though the proportion of streamflow declines attributed to temperature is less well understood [85,90,92]. However, Milly and Dunne [49] recently estimated that annual mean streamflow in the Colorado River Basin has declined by 9.3% for every degree Celsius of warming. This trend is driven by increased evapotranspiration largely as a result of snow loss and an associated decrease in albedo. Spatiotemporal differences in streamflow trends exist, where decreasing and neutral streamflow trends dominated at low elevation sites (<2300 m), while changes in streamflow center of timing were greater at higher elevation sites [89]. Thus, future studies should include data from streamgages more representative of conditions across the entire basin. The impacts of other drivers including dust-on-snow deposition, antecedent soil moisture, and changes in land use, water use, and vegetation on streamflow have been less studied, despite potentially relevant consequences [95]. These factors have impacts at local scales, but most studies have been conducted at large spatial scales. Limitations of existing studies, opportunities for new assessments, and justification for how these studies would enhance our understanding of water availability, in the basin are presented in Table 2.

Table 2. Limitations of existing streamflow trend assessments and opportunities for new water availability assessments.

Limitations of Existing Trend Assessments	Possible Directions to Expand Trend Assessments	Ways New Approach Could Enhance Understanding of Change and Processes Driving Change
Limited spatial extent. Existing studies are often limited in the number of sites or spatial extent over which they conduct trend assessments.	Analyze trends at a greater number of sites across the basin representative of different elevations, land uses (e.g., not just reference streams), and subbasins (e.g., Upper Green, Yampa-White, etc).	Trend analyses would include a basin-wide assessment of streamflow, including all sub-basins, tributaries, and reference sites, where possible. Additionally, having trend analyses at a denser spatial resolution will enable a more robust assessment of how and when streamflow changes in different UCOL subbasins.
Limited scope. Heavy focus on streamflow conditions most relevant to spring runoff (high and mean flows).	Assess trends in additional metrics including magnitude, duration, and frequency of low-streamflow events and high and mean streamflow events during summer periods.	Summer precipitation (monsoons) are important for moderating water demand for agriculture and urban outdoor use. Likewise, monsoon events and characteristics of low-streamflow are important to ecological functions.
Out of date. Current (2000–2021) temperature-driven drought is unprecedented in the gaged record.	Rapidly changing drivers of streamflow declines coupled with water demand exceeding supplies warrants regular updates to trend estimates.	Obtain a better understanding of the relationships among hydroclimatic and water use variables to improve water availability assessments.
Limited trend attribution. Heavy emphasis on how hydroclimatic variables influence streamflow to the detriment of other potentially important drivers.	Expand trend attribution investigations to assess the influence of other attributes, including large scale land use change, changes in water use driven by irrigation methods or population increases, and changes in vegetation, to better understand drivers of change.	An enhanced understanding of processes driving streamflow trends will inform resource managers seeking to mitigate the impacts of drivers, where possible, on declining streamflow.

3.2. Salinity in Groundwater and Surface Water

Dissolved solids (salinity) are an important water quality constituent in the UCOL in both groundwater and surface-water resources. As previously discussed, natural and anthropogenic sources, including sedimentary rocks and irrigation, contribute salinity to the Colorado River. High salinity levels in the River may cause corrosion damage and reduced agricultural yields, and they present challenges for Reclamation's delivery obligations of Colorado River water to Mexico.

3.2.1. Data

The data discovery effort for the UCOL focused on salinity measurements in surface water and groundwater. Total dissolved solids (TDS) concentration is the accepted measure of salinity, but specific conductance (SC) can often be used as a surrogate. Therefore, the availability of both TDS and SC data were evaluated. The survey of available data included discrete TDS measurements and discrete and continuous SC measurements.

The USGS and other governmental and non-governmental organizations have collected discrete TDS and SC data in the UCOL. More than 13,000 stations in the UCOL were identified with discrete TDS measurements and over 19,000 stations with discrete SC measurements—and most of those stations were operated by the USGS (74% where TDS was measured and 64% where SC was measured). About 90% of the salinity results from the UCOL represented surface-water conditions and about 10% represented groundwater conditions. Almost all the discrete TDS and SC data collected in the UCOL are available through the National Water Quality Monitoring Council Water Quality Portal (WQP) [96]. The WQP is a repository for the three primary databases for storing water-quality data in the U.S.—USGS NWIS, USDA Agricultural Research Service (ARS) [97], and the U.S. Environmental Protection Agency (USEPA) Water Quality Exchange [98], which has replaced the USEPA Storage and Retrieval (STORET) database that was decommissioned in 2018.

The USGS and a small number of other governmental and non-governmental organizations have collected continuous SC data at sites in the UCOL. While the USGS is the largest single source of continuous SC data, other agencies in aggregate are the source of much of the data. The USGS data are available from either NWIS [4] or the National Water Dashboard [27].

An initial review of the surface-water salinity results did not indicate substantial spatial bias within the UCOL. The TDS sample density, expressed as the total number of discrete samples per square kilometer, was used as an indicator of spatial coverage. Sample density was a more accurate indicator of spatial coverage than the distribution of individual monitoring sites (the approach used for the streamgages), because a large percentage of the water-quality sites had very few TDS samples (<10). The TDS sample density for each of the 60 8-digit HUC [99] watersheds in the UCOL was compared to two hydrologic characteristics for each HUC8 watershed: the NHDPlus stream length density (kilometer per square kilometer) and the mean annual runoff (millimeters per year) estimated by recent SPARROW modeling [52]. TDS sample density was positively, but weakly, related to both stream length density and mean annual runoff. It is logical to expect more water-quality sampling to occur in watersheds with greater stream density and mean annual runoff. But the weak correlation between those watershed characteristics and sample density suggests that watersheds with lower stream density and runoff (such as headwater areas and arid lands) also are well represented in the salinity data for the UCOL. Temporal analyses of the available data revealed that 70% of the historical surface-water TDS samples in the UCOL were collected in the 40 years between 1970 and 2009, with slightly lower numbers in the second half of that period compared to the first half. There were 55% fewer surface-water TDS samples, however, collected between 2000–2009 compared to 2010–2019. Seasonally, the greatest number of TDS samples were collected during summer and the lowest number of samples were collected during winter.

In contrast to the surface-water salinity results, there were clear spatial patterns in the distribution of the groundwater salinity results. For example, one-half of the groundwater

TDS samples were obtained from three river basins (the White and Yampa, the Lower Green, and the Colorado Headwaters) and these basins, in combination, make up about one-third of the total area of the UCOL. The greatest density of groundwater TDS samples was found in the White-Yampa River basin, which makes up 11% of the total area of the UCOL but contained 23% of all samples.

3.2.2. Modeling Capabilities

Ground Water

There are currently no known existing models that simulate groundwater salinity at the basin scale for the UCOL. At the sub-basin scale, the coupled Agricultural Policy/Environmental eXtender (APEX)-MODFLOW models [100] of the Animas and Price watersheds may be applied to simulate salinity in both the surface and subsurface, although at this time those simulations have not been published.

Surface Water

There are several modeling tools available for simulating salinity in surface water across the UCOL. Long-term average SPARROW models covering the UCOL for 1984–2012 have been developed for total dissolved solids [18,20]. Several RF models have been developed for the UCOL to estimate salinity yields and sources and test spatial calibration schemes for salinity load and yield models [101]. RF models have also been developed to explore the relationships between stream and catchment characteristics associated with stream sites where salinity is positively correlated with suspended-sediment concentrations and for predicting where those sites occur in unmonitored reaches [102].

The CRSS model (described more fully in Streamflow Section 3.1.2) includes a salinity module, which Reclamation uses to analyze salinity concentrations in UCOL streams and reservoirs [103]. The CRSS salinity module is intended for long-term salinity simulation (15–20 years) and is highly sensitive to initial conditions in the first 10–12 years [104]. Simulation results include annual average salinity concentrations at the numeric criteria stations downstream of Hoover Dam and Parker Dam and at Imperial Dam which can be used to analyze the probability of exceeding the numeric criteria in future years.

At the sub-basin scale, the Bureau of Land Management has worked in collaboration with the USDA ARS, USGS, NRCS, and universities to develop and refine regional watershed and water quality surface water modeling using the APEX model to quantify and assess sediment and salt transport in the UCOL [105]. APEX is a modeling tool designed to support management of farms and watersheds in obtaining sustainable farm production and maintaining environmental quality [106]. APEX supports evaluation of land management strategies considering sustainability, erosion, economics, water supply and quality, soil quality, plant competition, weather, and pests. MODFLOW has been coupled to APEX to simulate streamflow, groundwater levels, recharge, and groundwater-surface water interactions in the Animas River watershed in Colorado and the Price River watershed in Utah, with the intent to simulate salinity in both the surface and subsurface [100,107].

Both Reclamation and the USGS have developed salinity models for Lake Powell. Reclamation uses the CE-QUAL-WQ code to simulate hydrodynamics, temperature, salinity, dissolved oxygen, phytoplankton, and organic matter decay in Lake Powell [103]. CE-QUAL-W2 is a 2D water quality and hydrodynamic model for rivers, estuaries, lakes, reservoirs, and river basin systems. CE-QUAL-W2 simulates temperature-nutrient-algae-dissolved oxygen-organic matter and sediment relationships. QUAL2K, a 1D, steady state stream water quality model, has been used by Reclamation to simulate multiple constituents (streamflow, temperature, conductivity, nutrients, selenium) along segments of the Colorado River [108]. The USGS also has developed a multiple linear regression model of monthly dissolved solids inflows to Lake Powell for water years 1980–2016 [23]. The model was developed to provide Reclamation with advanced notice of changing salinity trends before they reach monitoring sites in the Lower Colorado River Basin. The model

estimates Lake Powell salinity as a function of main tributary streamflow, time, and basin average precipitation.

3.2.3. Trends

For surface water, numerous trend assessments of dissolved solids have been conducted over multiple decades to inform water and resource managers across the basin. Published dissolved-solids trends investigations for UCOL groundwater could not be found and may be due to the limited availability of dissolved-solids concentration data in groundwater [17]. Prior to applying trend tests, many studies used linear regressions to estimate daily dissolved-solids loads from observed streamflow and discrete or daily dissolved-solids concentrations or specific conductance data. Adjusting for the effects of streamflow was commonly achieved by computing a regression between streamflow and concentration or load, calculating the residuals of the regression, and using the residuals as flow-adjusted concentrations or flow-adjusted loads [109–113]. Subsequently, a variety of trend methods were applied to daily estimates to assess the magnitude and statistical significance of seasonal and/or annual dissolved solids change over a fixed period of analysis. Parametric and non-parametric trend techniques have been used to quantify dissolved-solids trends in the basin, and in many cases multiple trend techniques were applied in a single study [74]. In most cases, monotonic trends were used to evaluate dissolved-solids change between fixed starting and ending dates, but provided no information about the pattern of change through time. LOESS smooth curves were applied in some cases to better understand the evolving nature of dissolved-solids trends. Recent trend assessments use a newly developed tool, Weighted Regressions on Time, Discharge, and Season (WRTDS), to quantify changes in flow-normalized water quality concentrations and loads in streams, providing an opportunity to describe patterns of water quality change as they vary through time, season, and streamflow condition. WRTDS provides enhanced descriptions of change and diagnostic tools that provide useful information for resource managers seeking to improve water quality [114].

Overall, previous research has consistently shown declining trends in dissolved-solids concentrations and loads in UCOL streams from as early as the 1930s to the early 2000s [109–111,115–117]. Anning et al. [17] found decreasing dissolved-solids concentration trends from 1974 to 2003 at 80% of sites within the upper UCOL (Colorado headwaters, Gunnison, and Upper-Colorado-Dolores basins), at 68% of sites within the Green River Basin (Upper Green, Great Divide closed basin, White-Yampa, and Lower Green basins), and at 85% of sites within the San Juan River basin (Upper and Lower San Juan basins). In a recent assessment of national trends, Oelsner et al. [118] reported 6 out of 7 UCOL sites had decreasing trends in dissolved solids from 1972 to 2012. Placed in the context of the entire United States, the UCOL showed some of the most consistent decreases in dissolved-solids trends out of any region [115,118]. While multiple studies show consistent decreases across the basin for a variety of time periods, studies are limited by their region of analysis and time period of available data. A comprehensive assessment of dissolved-solids trends, including a variety of trend periods of interest and trend assessments for all sites with available data, is currently lacking.

Previous studies suggest that observed trends may be caused by trans-basin diversions, changes in land and water use, salinity-control activities, climate, and reservoir development [109,111,116,117]. For example, Butler [110] identified decreasing trends in dissolved-solids loads and concentrations near Grand Valley, Colorado from 1970 to 1993, concluding that trends were, in part, caused by mitigation efforts targeted at reducing salinity (i.e., salinity-control projects), but that natural or other anthropogenic effects in the UCOL likely also played a role in decreasing salinity. Decreases in dissolved solids observed upstream of salinity-control projects from 1970 to 1993 [113] and from 1986 to 2003 [112] support the idea that watershed processes, such as stream-channel evolution, hydrologic variation, changing land-use practices, or fluctuations in groundwater discharge and quality, also contributed to observed decreases. Additional trend analyses have

specifically investigated the effects of UCOL salinity-control projects [119,120], finding that salinity reductions coincide with areas where projects have been implemented upstream. Rumsey et al. [13] found decreasing trends in groundwater-discharged dissolved-solids loads at 17 out of 27 (63%) UCOL stream sites from 1986 to 2011, indicating processes related to the subsurface transport of salinity are changing over time. While there are many informed ideas about what has caused changes in dissolved solids in UCOL surface waters, no study to date has attempted to identify which watershed processes are the most important drivers of observed salinity change. Efforts to attribute salinity trends to specific watershed processes and to understand how drivers vary through time would advance understanding of salinity transport and inform integrated modeling efforts aimed at predicting future dissolved-solids conditions.

Previous trend assessments of dissolved solids in UCOL streams provide useful and consistent evaluations of dissolved-solids trends through time. Building on existing work, there are several opportunities to improve understanding and expand the application of dissolved-solids trends across the basin. Table 3 describes gaps and limitations of existing studies and lists possible directions for enhancing trend assessments.

Table 3. Gaps in existing dissolved-solids trend assessments and opportunities for enhancing assessments.

Limitations/Gaps in Existing Trend Assessments	Possible Directions to Expand Trend Assessments	Ways New Approach Could Enhance Understanding of Change and Processes Driving Change
Limited spatial extent. Existing studies are often limited in the number of sites or spatial extent over which they conduct dissolved-solids trend assessments. In many cases, the number of sites where trends were analyzed is less than 20, often excluding sub-basins and tributary streams.	Analyze trends at a greater number of sites across the basin. Dissolved-solids concentrations and streamflow data exist across the basin and could be applied more broadly to assess spatial patterns in trends.	Trend analyses would include a basin-wide assessment of dissolved solids, including all sub-basins, tributaries, and reference sites, where possible. Additionally, having trend analyses at a denser spatial resolution will enable a more robust assessment of how and when dissolved-solids change in different UCOL sub-areas.
Most studies report monotonic trends that provide no information about the patterns of dissolved-solids change through time.	Apply state-of-the-science trend evaluation methodology to estimate trend patterns through time.	Understanding the evolving patterns of how dissolved-solids change through time is useful for assessing drivers of change and understanding the changing rates of trends through time [114].
Trend assessments are out of date.	Automate analyses to update trends on an annual or seasonal basis so that trends are current and up-to-date.	A framework for providing up-to-date assessments of trend across the UCOL could help resource managers better understand changing water supplies and changing conditions in ecosystems. It would also provide an opportunity to continuously evaluate current conditions in the context of historical variability and long-term shifts.
Many trend assessments apply trend estimation techniques with no descriptive capabilities, limiting the amount of information that can be obtained from collected water quality and streamflow data.	Apply new, state-of-the science tools such as WRTDS to obtain trend outputs that not only identify trends, but describe the nature, rate, magnitude, and significance of dissolved-solids change.	Tools such as WRTDS provide robust estimates of trends that remove the year-to-year influence of streamflow, describe the changing nature of dissolved solids, apply a flexible modeling framework that does not assume the data follow a particular form, and allow water quality and streamflow relationships to evolve through time [114].

Table 3. Cont.

Limitations/Gaps in Existing Trend Assessments	Possible Directions to Expand Trend Assessments	Ways New Approach Could Enhance Understanding of Change and Processes Driving Change
Fixed trend periods. Many studies analyze trends between fixed starting/ending dates to meet specific study objectives. With updates to modeling and computing capabilities, trends could be modeled for any combination of trend periods provided adequate data are available.	Provide trends for all possible combinations of trend periods and make data visualization tools that allow for an adjustable time-period selection.	Trends for user-defined periods of interest allow trends to be more versatile and flexible to meet a range of resource manager and data user needs.
Limited integration of dissolved-solids trends with other watershed parameters. In some cases, dissolved-solids trends are assessed in conjunction with changes in streamflow and/or major ions, but largely efforts to integrate dissolved-solids trends with other watershed variables is limited.	Integrate dissolved-solids trends with other priority water availability components and across a greater number of sites in the basin.	Integration of trends from multiple watershed variables could help to expand understanding of how water quality, streamflow, groundwater, and reservoir conditions interact and affect dissolved solids in the UCOL, enabling users to begin evaluating change in the system as a whole, not as an assortment of individual components.
Most trends are generated on an annual basis.	Assess seasonal/monthly trends in dissolved solids, and/or trends during baseflow-dominated-seasons of the year.	Enhance understanding of seasonal changes in dissolved solids that could inform drivers of change.
Trends are not compared to benchmarks.	Put trends in context of benchmarks relevant for a wide variety of water uses (ecosystem, municipal supply, irrigation, industrial uses, etc.).	Obtain a better understanding of whether dissolved solids are trending toward conditions of concern.
Limited trend attribution. Several studies compare dissolved-solids trends to periods affected by watershed change (such as reservoir construction, salinity mitigation projects, mining, or other watershed activities), but a comprehensive assessment linking watershed changes to dissolved-solids trends has not been conducted.	Conduct a comprehensive trend attribution investigation to combine patterns of historical change in dissolved solids and watersheds attributes to better understand drivers of change.	An enhanced understanding of watershed processes driving dissolved-solids change will inform: 1. integrated modeling efforts and 2. resource managers seeking to mitigate the impacts of dissolved solids in the Colorado River.

3.3. Groundwater Levels and Storage

An understanding of the current and projected status of groundwater resources, along with trends in groundwater levels and storage, is an important component of water availability assessments in the UCOL from both a quantity and quality perspective. On average, groundwater discharging to streams makes up an estimated 56% of the flow in rivers and streams in the upper Colorado River Basin [12]. Groundwater in the UCOL also is an important source of water for direct use, where it provides nearly all self-supplied domestic water [24]. Higher salinity in groundwater than in runoff in major tributary catchments in the UCOL is responsible for increased salinity loads at stream monitoring sites during low-flow time periods [23]. Important ecosystems in the basin are sustained by groundwater discharge at spring sites. Projected recharge to UCOL groundwater systems is expected to decrease in some parts of the basin [121] which may result in reduced baseflow to streams and subsequently reduced streamflow [53].

3.3.1. Data

Almost all groundwater-level data for the UCOL are available from the USGS and the five basin states. Compared to the other priority water availability components, however, much of the data are poorly organized and documented. As a result, there might be some

useful groundwater-level data that have not been identified in this evaluation. The USGS serves groundwater-level data through both NWIS [4] and the National Ground-Water Monitoring Network (NGWMN) [122], which is a compilation of selected groundwater monitoring wells from Federal, State, and local groundwater monitoring networks across the United States. In addition, the basin states of Arizona [123], Colorado [124], Utah [125], and Wyoming [29] serve groundwater-level data, some of which are included in the USGS databases (e.g., all groundwater-level data collected by the state of New Mexico are stored in NWIS). The U.S. Department of Energy [32] has collected groundwater-level data for a small network of wells in the East River watershed in Colorado and these data also are publicly available.

3.3.2. Modeling Capabilities

Several available models can be used to simulate groundwater levels and storage across the UCOL. The USGS GSFLOW model of the UCOL couples a MODFLOW-2005 groundwater flow model with a PRMS surface water model (described previously) [46] and could provide estimates of steady-state and transient groundwater levels and storage across the basin. The UCOL has been subset from the CONUS-ParFlow model and coupled to the CLM land surface model to simulate steady state (1950–2000) and transient (three years at hourly time step, results focus on water-year 1983) energy and water balance in the subsurface [44].

There are several tools available for simulating groundwater at the sub-basin scale within the UCOL. There are MODFLOW models of smaller areas within the UCOL including Spanish Valley, Utah [126] and the San Juan Basin [127]. MODFLOW has also been coupled to APEX (described above) to simulate streamflow, groundwater levels, recharge, and groundwater-surface water interactions in the Animas River watershed in Colorado and the Price River watershed in Utah [100]. These models are coupled such that APEX simulates land surface hydrology, soil hydrology, and streamflow routing within the basin and MODFLOW simulates groundwater flow in a heterogeneous aquifer system and groundwater-surface water exchange along streams [100].

Several integrated hydrologic modeling efforts that include groundwater have focused on the East River watershed in Colorado (e.g., [128]). A ParFlow-CLM model of the East River in Colorado has also been developed for water-year 2006 (hourly time steps) to test the effect of changing spatial resolution on modeled processes [129]. Hydrologic parameters from this ParFlow-CLM model have been applied to the High-Altitude Nitrogen Suite of Models (HAN-SoMo), a watershed-scale ensemble of process-based models that quantifies sources, transformations, and sinks of geogenic and atmospheric nitrogen through the watershed [130]. A deep-learning emulator for ParFlow (ParFlow-ML) was developed for the Taylor River watershed, Colorado [131]. ParFlow-ML can emulate the ParFlow transient 3D integrated hydrologic model at much lower computational expense. The emulator is trained based on ParFlow simulations and takes physical parameters applied in the ParFlow model including topography, hydraulic conductivity, initial pressures, and precipitation inputs. The emulator produces spatially distributed, transient outputs of pressure head and relative saturation from which quantities such as streamflow, water table depth, and total water storage can be calculated. Amanzi-ATS is an integrated surface and subsurface reactive flow and transport model. Amanzi-ATS has been applied in the East River, Colorado to understand concentration-streamflow relationships under snowmelt and baseflow conditions [132].

3.3.3. Trends

Recent work highlighting the importance of groundwater in sustaining surface water flows [12], as well as projected increases in the use of groundwater to augment water supplies, emphasizes the need for more detailed study of trends in groundwater quantities in the UCOL. Trend assessments of groundwater quantity are limited in the UCOL and the estimated magnitude of change is inconsistent among existing studies [133–135]. Consider-

ing recent droughts and predicted changes in climate and demand for water, improving our understanding of trends in groundwater is essential.

In-situ groundwater data are spatially and temporally limited in the UCOL and no studies were found assessing trends of ground-based data from monitoring wells, although the Tillman and Leake [136] investigation of trends in Arizona groundwater levels in the lower basin may provide a useful model. Data collected from NASA's twin Gravity Recovery and Climate Experiment (GRACE) mission provide an opportunity to estimate terrestrial water storage, including groundwater, surface water, soil water, and snow water equivalent, from space through estimation of Earth's gravity field variations over time and space. The GRACE platform and its replacement, GRACE-FO, monitoring period is relatively short (2002–present), though extrapolating the data backward in time using monitoring and modeling data can provide longer-term context for the GRACE data [134]. Obtaining accurate estimates of groundwater storage using GRACE data requires disaggregating terrestrial water storage into different water budget compartments, where using all available data, including ground-based data, to constrain uncertainties in estimated water budgets is critical [134]. The number of groundwater monitoring wells used for comparison with GRACE estimates ranged from 2 to 18 across studies and a paucity of data available in the UCOL compared to the lower basin was apparent.

GRACE-derived groundwater storage estimates have been used to better understand responses of groundwater to drought and long- and short-term hydroclimatic variables in the UCOL [133–135]. Across all studies reviewed, decreasing [133,135] and no [134] trends in groundwater storage were reported across various timescales. Castle et al. [135] used GRACE estimates of terrestrial water storage to assess changes in groundwater storage and surface water storage during a period of sustained drought from 2004 to 2013. They assessed trends using a method that accounts for residual serial correlation and time series error across the entire time period of analysis and in shorter time periods that corresponded to specific hydroclimatic events. Groundwater storage accounted for the bulk of freshwater losses in the UCOL and lower basin. The steepest rate of groundwater decline followed exceptional drought conditions in 2012 and record low snowpack in the UCOL, highlighting the important connection between surface water availability and groundwater use. Similar temporal patterns of GRACE-derived groundwater storage estimates were described by Mafuzur Rahaman et al. [133]. In this study, spatial variation of Thiel Sen slope and significance of the trend in groundwater storage was assessed using the Mann-Kendall test. They identified that groundwater storage has undergone greater declines in the UCOL compared to the lower basin and that differences in recharge among the basins may explain the variability. Scanlon et al. [134] extended GRACE-derived data by reconstructing long-term estimates of total water storage from ground-based monitoring and modeling data to better understand how anthropogenic drivers and long-term climate (including drought indices, total precipitation, and values for El Nino/La Nina Southern Oscillation, Pacific Decadal Oscillation, and Atlantic Multidecadal Oscillation) influences changes in water storage. Relatively stable groundwater storage was found in the UCOL, thus trends were only presented for the lower basin. Differences in findings among studies likely stem from different processing techniques used for the GRACE data, including the type and amount of data used from groundwater level monitoring data. Given the lack of groundwater quantity trend assessments in the UCOL and the possible increasing reliance on this resource for water supplies in the future, there is a need for better understanding of groundwater trends in the basin. Limitations of existing studies, opportunities for improvement, and justification for how these studies could enhance understanding of water availability in the basin are presented in Table 4.

Table 4. Limitations of existing groundwater quantity trend assessments and opportunities to enhance understanding.

Limitations of Existing Trend Assessments	Possible Directions to Expand Trend Assessments	Ways New Approach Could Enhance Understanding of Change and Processes Driving Change
Limited spatial extent. Existing studies use estimated groundwater storage data.	Analyze trends at groundwater wells in the UCOL.	Trend analyses would include a basin-wide assessment of groundwater levels. Assessment of trends in groundwater levels could expand the spatial extent and inform changes in groundwater-surface water interaction.
Out of date. Current (2000–2021) temperature-driven drought is unprecedented in the gaged record.	Rapidly changing drivers of groundwater level trends, including hydroclimatic variables and water management operations, warrant regular updates to trend estimates.	Obtain a better understanding of the relationships among drivers to improve water availability assessments.
Limited trend attribution. Focus has mostly been on climate data.	Expand trend attribution investigations to assess the influence of anthropogenic factors, including groundwater withdrawals, especially during the recent drought period where groundwater withdrawals likely increased.	An enhanced understanding of processes driving river temperature trends could inform resource managers seeking to mitigate the impacts of drivers, where possible, on changing groundwater levels.

3.4. Snow

Precipitation in the UCOL occurs as both rain and snow and provides recharge to groundwater systems, runoff to streams and rivers, and water for vegetation use. Snow has a special importance in the basin and is the only climate driver covered in this review. As described previously, mountain snowpack and snowmelt play a critical role in the hydrology of the UCOL. High elevation areas in the upper basin receive most of the precipitation and are cold enough to allow the accumulation of seasonal snowpack [10]. These limited areas produce a large portion of the runoff to streams in the basin—about 15% of the surface area of the basin contributes about 85% of the average annual runoff [10]. Owing to the limited area contributing a majority of basin runoff, changes in precipitation (both amount and timing) in these relatively small areas can have a profound effect on resulting streamflow in the upper basin and subsequent reservoir storage throughout the basin. It is also likely that snow conditions contribute to the quasi-decadal-scale cycles of dissolved-solids concentrations in the Colorado River [23].

3.4.1. Data

The most common metric used to describe snowpack is snow water equivalent (SWE), which expresses the depth of water contained in the snow. The NRCS began manually measuring SWE at snow courses in the UCOL in 1930 [137]. These monthly measurements represent the longest SWE record available in the UCOL. There are 194 NRCS snow courses in the UCOL, and 54 of the sites remain active. The elevation of these snow courses ranges from 2149 to 3528 m with a median elevation of 2865 m. Starting in 1963, the NRCS began to replace snow course sites with automated Snow Telemetry Network (SNOTEL) sites that provide daily SWE measurements. There are 136 SNOTEL sites (135 active) in the UCOL at elevations of 2285 to 3539 m with a median of 2871 m [137]. There are also six USGS sites that provide daily SWE information [3].

SNOTEL and snow course sites are generally located in sheltered clearings in mid-elevation areas. These measurements are not representative of lower elevation ephemeral snowpacks and higher elevation alpine areas. This makes it difficult to extend these point measurements to the watershed scale. Remote sensing efforts aim to fill this gap by measuring snow properties at a larger scale. The MODIS satellite platform has provided

global 500-m 8-day snow covered area since 2000, and the LANDSAT satellite platform has provided global 30-m 16-day snow covered area (SCA) since 1984. Since these satellite products do not measure SWE, their ability to quantify how much water the snowpack holds is limited. Airborne Snow Observatories (ASO) provide a more direct SWE estimate by using modelled snow density and scanning lidar depth measurements to create a gridded 50 m SWE product. ASO flights typically occur in late winter and have been completed throughout the western United States since 2013.

3.4.2. Modeling Capabilities

Because most of the UCOL surface and groundwater water originates as snow, model representation of snow and associated processes including accumulation, redistribution, sublimation, melt, runoff and recharge, is important. Given the high correlation between melt and air temperatures [138], attributed to the high correlation between temperature and several energy balance components, temperature-index models assume a relationship between snow and air temperatures to simulate snowpack [139]. Statistical models estimate relationships between snow and other explanatory variables to predict snow characteristics (often SWE over an area) and can include a range of approaches including regression-type models, machine learning methods, and interpolation procedures. Physically based, mass and energy balance approaches can outperform temperature index models in representing snowpack spatial variability, snowpack at fine temporal resolution [139,140], or energy balance [141], but often require highly accurate forcing data that may not be available. Temperature-index models often have lower data requirements that can make them more widely useable and have also been shown to outperform process-based models in some cases [139]. Statistical models are widely used because of their simplicity and ease of use, and they can produce results that generally agree with physically based models [142].

At the national scale, snow is simulated with both process-based and machine learning models. The NOHRSC Snow Model (NSM) [143] is used by NOAA's National Operational Hydrologic Remote Sensing Center (NOHRSC) in the SNOw Data Assimilation System (SNODAS) project [144]. The NSM is a physically based, spatially distributed multi-layer model that simulates snow accumulation and ablation. NSM simulates snow mass and energy balance and is used with downscaled meteorological information and data assimilation that updates snowpack estimates using ground and air-based observations to produce 1 km resolution SNODAS products. Clow et al. [145] showed that SNODAS performs poorly in alpine areas but can be greatly improved by applying wind redistribution post-processing.

PRMS, as implemented in the NHM, simulates seasonal snowpack initiation, accumulation, and depletion across the continental United States according to water mass and energy balance. The snow module results include snowmelt, snow depth, density, SWE, free water content, temperature, albedo, sublimation, and cover area, and meltwater output gets transported to runoff or soil moisture within the model [36]. Albedo is calculated as a function of time since the last snowfall and is reset to a maximum value upon new snow events. Snowpack energy exchange is primarily controlled by snow-atmosphere interactions and snowpack conduction. At the snow surface, energy exchange is governed by radiation budgets calculated as a function of either degree-days, sky cover and temperature, or measured radiation. Snowmelt occurs when snow temperatures are above 0 °C and the total energy flux to the snowpack is positive. Snow covered area is determined using a depletion curve relationship to SWE. Sextone et al. [146] found that simulated runoff was sensitive to this depletion curve, and that runoff was most sensitive to changing snowmelt in areas with high snow persistence and peak SWE:annual-precipitation ratios.

The Snow Water Artificial Neural Network Modeling System (SWANN) includes SWE back to 1980 for the CONUS [147,148]. More details are provided in the Snow Data Section 3.4.1. The ratio of SWE to net snowfall from SNOTEL and COOP sites is used to interpolate SWE and snow depth across an area. The national dataset assimilates these in-situ SNOTEL and COOP snow measurements with modeled, gridded temperature and

precipitation data from PRISM and a physically based snow density model [149] to predict SWE and snow depth across the country [150]. Precipitation phase and snow ablation are determined by air temperature thresholds.

Within the NWM, snow characteristics, including SWE, snow depth, SCA, and others, are simulated according to mass and energy balance constraints in the land surface model Noah-MP, which has multiple parameterization options (MP) [151,152]. Noah-MP includes a three-layer snow model that simulates snow accumulation, snow freezing and melt, densification, and meltwater movement within the snowpack [152]. Snow interception by, and sublimation from, vegetation is also considered [153]. Noah-MP, as part of the NWM, has been applied under a variety of configurations to predict snow across the United States. In an evaluation of snow simulations in the UCOL, Minder et al. [154] suggest that the exclusion of dust effects on snow albedo within Noah-MP may bias springtime surface albedo and surface energy budgets that subsequently affect snowmelt, temperature, and snowpack evolution (this may apply to other models that do not consider dust on snow effects as well).

A range of physically based, temperature index, and statistical models have been applied at the regional or basin scale that includes the UCOL. VIC (described previously) simulates snow accumulation and melt as part of the more comprehensive hydrologic simulation. VIC is a multilayer model that uses an energy balance approach, and considers vegetative cover and interception, and elevation. Changes in SWE across the western United States were projected by applying historical and future projections of climate to the VIC model [155]. Vano et al. [156] compare the results of VIC simulations against four other land surface models over a historical time period to quantify sensitivity of UCOL runoff to precipitation and temperature perturbations.

Surface processes including snow are simulated within the CLM component of the coupled ParFlow-CLM model according to mass and energy balance constraints. The model requires meteorological variables including energy balance variables. Processes include thermal, vegetative processes, canopy interception, snow albedo changes, compaction, sublimation, and melt. Snow albedo decays with time and as a function of solar zenith angle. Snow variables (monthly averaged SWE, peak SWE, and time to total melt) in ParFlow-CLM are more sensitive to forcing parameters than snow input parameters, emphasizing the importance of accurate meteorological forcings and correct albedo parameterization [157]. In the UCOL, ParFlow-CLM simulation of snow-covered area and SWE tend to agree with snow observations [45].

SnowClim is a computationally efficient, fully distributed, process-based model with some empirical simplifications that simulates snow over large spatial domains at high-resolution according to mass and energy-balance constraints [158]. Because the model was designed for large spatial domains, it is a single-layer model that does not simulate effects of snow transport, vegetation, or fractional snow cover. It has been used to simulate snow (including SWE, snow depth, and snow duration) across the western United States at 210-m resolution for preindustrial (1850–1879), historical (2000–2013), and projected future (2017–2100) time periods.

Temperature-index models have also been used for operational snow forecasting across the UCOL. SNOW-17 is a temperature-index snow accumulation and ablation model, where temperature is the primary energy source for changes in the snowpack [159,160]. SNOW-17 accounts for heat storage, liquid water retention and transmission in the snowpack [161]. As a temperature-index model, it can be applied in environments prone to data scarcity [162], but temperature-index relationships may not apply under conditions of non-stationarity. SNOW-17 accounts for elevation-dependent differences in temperature affecting the snowpack, but does not account for differences in vegetation, topography, or dust loading which are important factors that influence solar radiation [162–164].

SNOW-17 is coupled to a runoff model, SAC-SMA, for CBRFC operational streamflow forecasting (previously described in the Streamflow section). SNOW-17 has also been used for other snow research. Slater et al. [165] used a simplified version of SNOW-17 to evaluate

sensitivity of SWE reconstruction across the western United States. Bryant et al. [164] used SNOW-17 and SAC-SMA to identify the error in streamflow prediction caused by dust radiative forcing on the snowpack in Senator Beck Basin, Colorado. Vano et al. [156] compared the results of SAC-SMA and SNOW-17 simulations against four other land surface models over a historical time period to quantify sensitivity of UCOL runoff to precipitation and temperature perturbations.

The MWBM (introduced in the Streamflow Modeling Capabilities Section 3.1.2. above), simulates snow accumulation and melt as functions of precipitation and temperature on a monthly time step [166]. Results of snow calculations are used to quantify subsequent hydrologic processes including runoff, storage and evapotranspiration. The MWBM has been used in several studies to quantify UCOL streamflow sensitivity to temperature rise [48]. Milly and Dunn [49] updated the MWBM to use a more physically based formulation of potential evapotranspiration, to allow snow sublimation, and to use a conventional degree-day treatment of snow melt in order to quantify sensitivity of streamflow to climate warming.

At the regional or basin scale, a range of statistical models have been developed and applied to study areas including the UCOL. A range of regression-based models, often paired with interpolation techniques, have been applied to predict SWE and other snow metrics such as snow depth, peak SWE, April 1st SWE, and snow residence times at points and across the UCOL [167–171].

Application of the linear regression model methods developed in Schneider and Molotch [168], which integrates observed SWE, satellite derived SCA, physiographic information, and reconstructed historical daily SWE from an energy balance model, includes prediction of near real time (approximately every two weeks) SWE maps at 500 m resolution for the Intermountain West region [172]. The historical daily SWE [173,174] is calculated using snowmelt estimates derived using a degree-day method in conjunction with satellite-derived SCA data to reconstruct the daily SWE for an area.

A variety of physically based, temperature-index, and statistical snow models have been applied in the UCOL at sub-basin or point scales. The Snow THERmal Model (SNTHERM) is a one-dimensional mass and energy balance multilayer thermal model that simulates temperature profiles, transport of liquid water and water vapor, snow accumulation, ablation, densification, and metamorphosis [175]. SNTHERM was used to simulate snowpack in Senator Beck Basin, Colorado [176]. Hourly meteorological data were applied to the model to simulate SWE, snow depth, and bulk snow density for WY 2006–2012. Prediction errors were attributed to a lack of wind transport representation in alpine areas and a warm bias associated with the modeled energy balance.

The snowcover energy and mass-balance model (SNOBAL) [177] is a physically based model that simulates the development and melting of seasonal snow cover at points or across areas (iSNOBAL). SNOBAL and iSNOBAL have been used in the UCOL to study dust radiative forcing effects on snowmelt (e.g., [163,178–180]). The NASA/Jet Propulsion Laboratory Airborne Snow Observatory (ASO) performs airborne snow surveys over UCOL subbasins to estimate high-frequency spatially distributed SWE and albedo estimates over large mountain basins to quantify the volume of water stored in seasonal snowpack. ASO uses snow depths simulated with iSNOBAL, in conjunction with lidar-derived snow depths and imaging spectrometer derived snow albedo to estimate spatially distributed SWE and other snow metrics [181,182]. Efforts to incorporate iSNOBAL into operational river forecasting with the CBRFC show promise and highlight the need for continued improvements to energy balance calculations [183].

SnowModel is a spatially distributed snowpack evolution model that prepares meteorological data, calculates the surface energy balance exchange, and simulates snowpack (SWE and snow depth), including wind transport, and runoff [184]. Snowpack is simulated using a single layer snowpack evolution model that responds to precipitation and melt fluxes, and accounts for compaction and temperature-based changes in snow-density. SnowModel has been applied in the UCOL to investigate the role of sublimation on snowpack and effects of forest and climate change [185].

The Utah Energy Balance (UEB) model is a single-layer physically based energy and mass balance model that simulates snowpack accumulation and melt on sub-daily time steps [186]. In the UCOL, UEB has been coupled with the SAC-SMA hydrologic model, and SWE data assimilation implemented, to improve streamflow forecasting [187]. UEB has also been evaluated in the UCOL watersheds for potential inclusion into the CBRFC National Weather Service River Forecasting System, as a process-based, energy balance model replacement for the temperature-index snow model, SNOW-17 [188].

Bair et al. [189] developed a new broadband snow albedo model as an alternative to the albedo decay equation typically used in physically based snowmelt models and applied it at two mountainous sites in the UCOL. Broadband albedo is computed using the spectral albedo (obtained from satellite-derived snow properties and illumination angle), a solar spectrum parameterization, and a statistical fit of an atmospheric radiative transfer model. Remotely sensed snow albedos were found to be more accurate than those derived from aged-based albedo decay models [189]. Scaling-improved representation of snow albedo to the basin scale may improve prediction of snowmelt and subsequent hydrologic processes.

Temperature-index models have been applied to areas within the UCOL. The Snow Runoff Model (SRM) [190] is a semi-distributed, temperature-index model that uses a recession flow calculation along with proportions of runoff derived from precipitation and snowmelt to simulate daily streamflow. SRM has been applied in small basins throughout the UCOL [190]. Day [191] evaluated future snowmelt and runoff in the Animas River Basin, Colorado using the SRM by applying future climate projections to a calibrated model of historical conditions.

The radiation-derived temperature index (RTI) model uses spatially varying proxy temperatures derived from the radiation balance to simulate snowpacks [192]. RTI has been implemented within the Gridded Surface Subsurface Hydrologic Analysis (GSSHA) model, which is a fully distributed, physically based, hydrologic model. GSSHA can implement either an energy-balance or temperature-index method to simulate snowmelt; the temperature-index (TI) method is based on SNOW-17 methods. The RTI method was added to GSSHA and tested within Senator Beck Basin, where it showed improved SCA prediction over the temperature-index method [192]. Use of the RTI model also produces more accurate streamflow estimates (including flow volume and peak flow rate) than the TI model, likely because the RTI model better reproduces spatial variability of SWE across the watershed [162].

Statistical models have also been developed and applied in the UCOL. Binary regression tree models, which can produce the most accurate estimates of distributed SWE when abundant field observations are available, use physiographic variables to predict snow depth or SWE [193]. In the UCOL, Meromy et al. [194] interpolated observations of snow depth with binary regression tree models at various spatial scales to evaluate biases between point-scale SWE (at SNOTEL stations) and SWE in the vicinity of the station. They used elevation, clear sky index, potential incoming solar radiation, percent canopy cover, slope, aspect, and maximum upwind slope as their independent variables. The regression tree outputs a spatially continuous snow depth at 30-m resolution given the inputs at the snow station centroid [194].

3.4.3. Trends

Substantial effort has been focused on understanding changes in snow processes in the western United States. Increased winter temperatures and shifts from snow to rain have led to smaller snowpacks [195], earlier snowmelt [196], slower spring snowmelt rates [197], increased mid-winter ablation [196], and decreased snow-covered extent [198]. Changes in snowpack size have been studied using SWE at either maximum accumulation or at a fixed date each year, commonly April 1st. Changes in melt timing have been considered using date of peak SWE, snowmelt center of mass, and snow disappearance date. Previous work has typically only focused on a few of these metrics at a time when assessing snowpack trends, though the choice of metrics can significantly impact what conclusions are drawn

from a trend analysis [199]. For example, decreases in peak SWE have been limited and spatially variable [196], but increases in mid-winter ablation have been larger and more widespread [199].

Snowpack trends are further complicated by several scale dependent processes that affect the sensitivity of snowpacks to warming at anywhere from the micro to continental scales. At the continental scale, natural variability in atmospheric circulation patterns has limited the effect of warming on snowpacks [200], and humidity has been shown to control sensitivity to warming [201]. At the meso scale, elevation-based temperature gradients have been shown to control the sensitivity of snowpacks to warming with lower elevation sites being more sensitive to warming [198,199]. Finally, at the micro scale, forest management [202] and beetle kill [203] have large effects on snowpack dynamics. The scale dependent nature of these processes highlights the importance of considering snowpack trends at a variety of spatial scales.

Previous work has considered snowpack trends over multiple time periods. Although some work has been completed using snow course data dating back to the 1930s [204], most work has typically used SNOTEL data [88,199,205] or SNOTEL derived data [198]. Since the SNOTEL network was completed in the early 1980s, this limits analysis to the past 40 years. Using this shorter record makes it difficult to separate the effects of natural interannual and interdecadal variability from long term climate effects. For example, since the 1980s natural variability in atmospheric circulation patterns has likely lessened the effects of long-term warming on snowpack dynamics [200]. These intricacies suggest that there is value in using multiple data sets for trends work and performing analyses over multiple time periods. Limitations of existing studies, opportunities for expanded assessments, and justification for how these studies could enhance understanding of water availability in the basin are presented in Table 5.

Table 5. Limitations of existing snowpack and climate trend assessments and opportunities to enhance assessments.

Limitations of Existing Trend Assessments	Possible Directions to Expand Trend Assessments	Ways New Approach Could Enhance Understanding of Change and Processes Driving Change
Limited spatial extent. Existing studies are often conducted at a broad spatial scale.	Analyze trends at a greater number of sites (or area if using raster data) across the basin representative of different elevations, land uses, and subbasins (e.g., Upper Green, Yampa-White, etc).	Trend analyses could include a basin-wide assessment of snowpack and related climate metrics. Additionally, having trend analyses at a denser spatial resolution could enable a more robust assessment of how and when snowpack changes in different UCOL subbasins.
Limited scope. Few snowpack metrics assessed at same time in existing studies.	Assess trends in multiple metrics (e.g., related to timing, total, precipitation).	Better understand how spatial variability across the basin, including differences in topography, elevation, and land use, influences trends in snowpack.
Limited understanding of how trends in snowpack influence water availability, as influenced by water quality.	Expand trend investigations to assess the influence of changes in snowpack to changes in salinity.	An enhanced understanding of processes driving snowpack trends will inform resource managers seeking to mitigate the impacts of drivers, where possible, on salinity.

4. Summary and Conclusions

The Colorado River in the southwestern United States supplies drinking water for 40 million people in the U.S. and Mexico, water for irrigation of 2.2 million hectares of land, and is an essential source of water for at least 22 federally recognized tribes [1]. The Colorado River Compact of 1922 [2] divided the Colorado River into upper and lower basins at the compact point of Lee Ferry, Arizona. About 90% of the flow in the lower

Colorado River at Lake Mead originates in the upper basin [4]. Extended drought in the basin and the prospect of an even warmer climate in the future pose challenges for water managers to deliver on compact and treaty promises. Limited water availability in the future also will continue to negatively affect aquatic ecosystems and wildlife that depend upon them. Advancing scientific understanding and predictive capabilities of water availability in the upper basin is essential to provide assessments of water availability relevant to a range of water users from water managers to the general public.

Water availability components of special importance (priority components) in the UCOL include streamflow, salinity in groundwater and surface water, groundwater levels and storage, and the role of snow in the UCOL water cycle. This manuscript provides a summary of current “state of the science” for each of these UCOL priority water availability components with a focus on identifying gaps in data, modeling, and trends in the basin. Trends provide context for evaluations of current conditions and motivation for further investigation and modeling, models allow for investigation of processes and projections of future water availability, and data support both efforts.

While the data for the UCOL priority water components are generally easily accessible from on-line sources (Table S1 in the Supplementary Material), these databases are maintained by many different organizations. In addition, unlike the other priority water components, groundwater level data are often poorly organized, not well documented, and only available upon request from individual agencies. Therefore, a centralized, well-organized clearinghouse that provides easy access to all data could be a valuable contribution to ongoing hydrologic studies in the region. This review also identified deficiencies and biases in the streamflow, salinity, and snow data that could limit their usefulness in some watershed assessments.

To comprehensively assess water availability in the UCOL, major gaps in modeling capabilities and applications need to be addressed (Table 6). Gaps include a separation of human and natural systems, and many models do not represent the entire basin. Such gaps are common to many sub-disciplines addressing questions of water availability. Fully integrated hydrologic models such as GSFLOW and ParFlow do not include critical human alterations to hydrologic systems including reservoirs and water management, nor have they been applied to questions of basin-wide water quality. Management and planning models such as CRSS and WEAP lack complexity in hydrologic representation that may hinder their usefulness under changing climate and land cover and use. Available water-quality models incorporate hydrology but are generally applied at small areas or over long-term mean conditions.

Published investigations of trends in groundwater levels and salinity are largely absent due to a lack of data availability. Basin-wide assessments, including all sub-basins, tributaries, and reference sites, with a unified period of analysis, including sub-annual assessments, of all water availability components could enable a more robust assessment of where, how, and when changes are occurring. Trends in streamflow and surface-water salinity need to be put in context of existing, and potentially new, benchmarks relevant for a wide variety of water uses (e.g., ecosystem, municipal supply, irrigation, industrial uses). Lastly, more effort is needed to integrate trends in all water availability components to expand understanding of how they interact.

Understanding gaps in available data and current capabilities in trends assessments and modeling in the basin is vital for planning science activities for future integrated assessments of water availability in the UCOL. Scientists and policymakers from many government agencies, academic institutions, and non-governmental organizations are currently “working the problem” of water availability in the UCOL. It will take ideas and strategies from across a wide range of subject areas and perspectives to ensure the adequacy of water resources in the basin going forward.

Table 6. Limitations of existing modeling abilities and opportunities for enhancement.

Limitations of Existing Modeling Capabilities	Possible Directions to Improve Modeling Abilities	Ways Improvements Could Enhance Prediction
Scaling: large-scale models may be less accurate or neglect important processes at fine spatial scales yet small-scale models don't provide information over larger areas necessary for basin-wide water availability assessments.	Include processes that are important at small scales in large-scale models as computational abilities improve, explore data-driven and hybrid approaches to prediction at a range of scales.	Improved prediction at a range of spatial scales.
Separation between natural and human systems. Many models don't represent both natural and human processes that affect water availability.	Integrate human systems including reservoirs, water use, diversions, water rights, land cover and use, and other human effects into hydrologic models.	Improve process understanding, relevance to land and water management, and applicability for near-term forecasting, long-term projections, and scenario-testing.
Separation between water quantity and water quality modeling.	Integrate water quantity and quality models.	Provide a more comprehensive assessment of water availability for a wider range of water users.
Separation between surface and subsurface systems. Although some models consider both, many do not.	Integrate surface and subsurface models.	Provide a more comprehensive assessment of water availability for a wider range of water users. Improve process-understanding and applicability for long-term projections and scenario-testing.
Lack of process representation or data on key processes limits applicability of some models. While this may depend on the purpose of the model, lack of, or poor, process representation can reduce prediction accuracy. For data-driven models specifically, it can also reduce explainability.	Depending on the model purpose, add relevant processes or data representing processes. This could include improved representation of snowpack and groundwater-surface water interactions, and related processes. For data-driven models, consider methods to improve explainability.	Improved prediction accuracy, explainability, and relevance to near-term forecasting and long-term projections.
Uncertainty about modeling approach.	Test multiple modeling approaches with common datasets to understand the effects of modeling decisions and representations.	Results would indicate how modeling decisions influence predictions and interpretation of results.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/w14233813/s1>, Table S1: UCOL Data Catalogue.

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