Salinity Management in the Upper Colorado River Basin: Modeling, Monitoring, and Cost-Equity Challenges

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SALINITY MANAGEMENT IN THE UPPER COLORADO RIVER BASIN:
MODELING, MONITORING, AND COST-EQUITY CHALLENGES

by

Jongho Keum

A dissertation submitted in partial fulfillment
of the requirements for the degree
of
DOCTOR OF PHILOSOPHY
in
Civil and Environmental Engineering

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2014
Salinity Management in the Upper Colorado River Basin: 
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by

Jongho Keum, Doctor of Philosophy
Utah State University, 2014

Major Professor: Dr. Jagath J. Kaluarachchi
Department: Civil and Environmental Engineering

Salinity has a significant influence on the community in the Colorado River Basin. In 2010, excessively saline Colorado River water caused an estimated $295 million in damages to agriculture, municipalities, and industries. Understanding the behavior of salinity and evaluating the effective managements are of great importance. Widespread saline geological structures in the Upper Colorado River Basin (UCRB) have led to its identification as the major salinity contributor to the basin while the Lower Colorado River Basin has become the major user of the impaired water. Salinity source and transport within the UCRB have received attention, specifically with the water quality model SPARROW. However, previous SPARROW salinity models for the UCRB were calibrated with data from the SPARROW 1991 model, and were only available through 1998 due to lack of data. Given these factors, the key motivation of this dissertation is to extend the previous model and to plan for the effective management of
This dissertation presents three key components for salinity management in the UCRB in three manuscripts. In the first manuscript, SPARROW salinity model in the UCRB are extended to cover 1999 to 2011. These models employ alternative data gathering procedures from readily available datasets. The importance of calibration approach and uncertainty analysis is presented. The second manuscript reports on the development of a methodology to predict the adequate number and locations of water quality monitoring stations. The level of monitoring is defined by an index, called station ratio (SR), which represents the relationship between the number of monitoring stations and the incremental water quality load within a watershed. The SR identifies monitoring redundancy or scarcity in a large basin. In the third manuscript, a practical framework to allocate the salinity control is developed by considering cost effectiveness, equity among stakeholders in each watershed, and their trade-offs. The trade-off curve defines the control costs to achieve a given level of equity, so that decision-makers can take into consideration not only control cost but also management equity.

This comprehensive framework provides the ability to simulate salinity sources and transport in the UCRB, and to evaluate both effectiveness of monitoring network and equitable allocation of the control responsibility. This framework allows decision-makers to manage salinity in the UCRB more effectively. However, this framework is not limited to the management of salinity in the UCRB only, and can be applied to other management problems.

(159 pages)
PUBLIC ABSTRACT

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Salinity issues in the Upper Colorado River Basin have been a serious concern to the western United States and northern Mexico. The Colorado River salinity is mainly come from geologic materials located in the Upper Colorado River Basin. Natural weathering and human activities, such as irrigation, accelerate the dissolution of saline materials. Economic damages due to salinity in the Colorado River Basin are estimated at $295 million in 2010, for example, reduced crop yield, plugging of water pipes and fixtures, and ecological health of rivers. In order to manage salinity in the Upper Colorado River Basin, SPARROW model has been applied to simulate salinity sources and transport. However, the model application discontinued during recent past due to lack of data. Given the motivation and importance of salinity issues in the Colorado River Basin, the overall goal of this research is to develop a decision-making framework for an effective salinity management in the Upper Colorado River Basin.
First, this research introduced a methodology for reliable analysis of salinity sources and transport in the Upper Colorado River Basin. However, recent decreasing trend of number of monitoring stations may cause increase of model uncertainty. Therefore, a decision-making methodology for an effective water quality monitoring network was developed. From the results of monitoring network analysis, the redundancy or scarcity of monitoring stations in each watershed can be identified under the given operational costs. Finally, salinity management scenarios considering cost and equity were developed. Management options considering cost only can neglect the fairness in the allocation of salinity control responsibilities among stakeholders. To overcome this limitation in management, the methodology developed in this research considers cost of salinity control, equitable distributions among stakeholders, and cost efficiency.

The methodologies developed in this research provide a comprehensive decision-making framework for an effective salinity management in the Upper Colorado River Basin. Moreover, this framework is not limited to the management of salinity in the Upper Colorado River only, but also can be applied to other water quality management problems.
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Most importantly, I am deeply thankful for the love and encouragement from my family. My dear mother and father’s prayers throughout my life have made all the progress possible. Finally, I wish to dedicate this work to my lovely son Ian.

Thank God.

Jongho Keum
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CHAPTER 1

INTRODUCTION

Motivation

The amount of usable water, such as surface water in rivers and lakes or ground water, is very limited, even though more than half of the Earth’s surface is covered by water. Moreover, radical social evolution during the recent centuries has led to significant increases in water demands that can cause serious conflicts between stakeholders. Given the importance and scarcity of water, management of water resources and water quality has become important. The amount of available water and its distribution to satisfy water demands have typically been addressed through water resources planning and management, while water quality management focuses on maintaining the usability of water. Salinity, defined as the amount of total dissolved-solids in a unit of water volume, is one of the common contaminants in water. For the management purposes, salinity is often represented as salt load in mass. There are two primary sources of saline water; sea water and natural geology. Sea water intrusion results in depletion of fresh water and becomes more severe with excessive use of fresh groundwater near the coastal area. River salinity is typically caused by weathering of natural geology where the soils and rocks are from an ancient ocean.

The Colorado River has some of the worst salinity issues in the world. A semiarid environment, coupled with significant social development, renders the Colorado River Basin to be a good example for the needs of water quality management as well as water resources management. The Colorado River System covers 620,000 square kilometers of basin area, and provides municipal water to nearly 36 million people and irrigation water
for 5.5 million acres of agricultural lands (US Department of the Interior, 2013). The municipal water uses include deliveries to the residential, commercial, and industrial sectors in the Colorado River Basin, and trans-basin diversions (Cohen, 2011; Colorado River Basin Salinity Control Forum, 2011). The Colorado River water consumers are distributed over parts of the western United States and northern Mexico. Highly saline Colorado River water has been a long-standing problem in the United States and Mexico causing international and interstate conflicts.

The Colorado River is naturally saline because of its geologic conditions (Miller et al., 1986; Timothy et al., 1988; Hayes, 1995; Patrick, 2000; Tuttle and Grauch, 2009). Mancos Shale, which is pervasive in the Upper Colorado River Basin, formed from sedimentation at the bottom of an ancient sea, and is considered the primary geologic material that makes the Colorado River saline (Miller et al., 1986; Timothy et al., 1988; Hayes, 1995; Tuttle and Grauch, 2009). In specific, geochemical interactions of water from precipitation and irrigation with the saline soil, alluvium, and rock formations contribute to the release of saline ions to ground and surface waters (Watts and Teel, 2003; Tuttle and Grauch, 2009). Therefore, salinity in the Colorado River, and the consequential socioeconomic damages on agriculture, municipalities and industries, are unavoidable. While the major source of the saline ions is widespread geologic materials in the Upper Colorado River Basin, the users of the impaired water are mainly located in the Lower Colorado River Basin. The examples of the salt damages consist of reduced crop production and clogging or etching of water pipe and structures (Houk et al., 2006, US Department of the Interior, 2013). The total salt damages in the Colorado River for
2010 were estimated at $295 million (US Department of the Interior, 2013).

Given the importance of salinity issues in the Colorado River Basin, the Colorado River Basin Salinity Control Forum (the Forum) was established by the seven US states; Arizona, California, Colorado, Nevada, New Mexico, Utah, and Wyoming. The Forum proposed numeric criteria and a plan of implementation, which adopted by the seven states, and approved by the US Environmental Protection Agency in 1975 (Colorado River Basin Salinity Control Forum, 1975, 2011). The numeric criteria were provided as flow weighted average annual salinity concentrations in 1972 at three locations along the Lower Colorado River; 723 mg/L below Hoover Dam, 747 mg/L below Parker Dam, and 879 mg/L at Imperial Dam, respectively. The plan of implementation (i.e. salinity control programs) has been established to mitigate socioeconomic damages caused by excessive salinity in the Colorado River. Salinity concentration in the Colorado River has remained below the numeric criteria due to the prior plan of implementation; however, the probability of exceeding the criteria will increase significantly without any further salinity control programs (Colorado River Basin Salinity Control Forum, 2011). Therefore, there is a need for a comprehensive framework providing effective salinity management scenarios in the Colorado River Basin.

Outline of This Study

Given the motivation and the importance of salinity issues, the overall goal of this dissertation is to develop a decision-making framework for an effective salinity management in the Upper Colorado River Basin. The three key components of this dissertation are; to extend the current understanding of salinity sources and transport in
the Upper Colorado River Basin using SPARROW simulation; to develop a methodology for an effective water quality monitoring network; and to develop salinity management scenarios that consider not only control cost, but equity, and their trade-offs. Each of these components is described in Chapters 2 through 4, and the summary. Conclusions and recommendations are outlined in Chapter 5. The specific objectives and tasks required to achieve the overall goal are as follows:

I. Analysis of salinity sources and transport in the Upper Colorado River Basin with emphasis on modeling, calibration, and uncertainty consideration.

   a. Gather the existing SPARROW database and other available data from various local, state and federal agencies to produce a single comprehensive database of salinity and hydrologic information.

   b. For locations and periods where hydrologic database are not available, identify and apply available prediction methods to complete the hydrologic database.

   c. Perform necessary model calibration and verification with SPARROW to predict salinity in the Upper Colorado River Basin, and identify any limitations of the modeling approach.

   d. Determine the trends of incremental loads from individual watersheds to rank watersheds for salinity production.

   e. Determine the impact of model uncertainty on overall salinity prediction.

II. Development of a decision-making methodology for an effective water quality
monitoring network.

a. Estimate the optimal number of monitoring stations for salinity modeling using different decision-relevant scenarios.

b. Identify the appropriate watersheds for the estimated number of monitoring stations to improve model accuracy.

c. Suggest potential options for the redistribution of monitoring stations considering limited operational costs.

III. Salinity management in the Upper Colorado River Basin with cost-equity considerations

a. Determine the relationship between salinity control costs and water quality targets

b. Establish equity criteria and measures

c. Develop scenarios of allocation of salinity control responsibilities

d. Estimate and compare the cost and equity for each scenario

e. Estimate the effectiveness considering cost, equity and their trade-offs

Chapter 2 extends the existing SPARROW salinity model in the Upper Colorado River Basin and revises the calibration approach. Uncertainty effects on salinity simulation are analyzed to rank and identify the vulnerable watersheds for salinity controls. Chapter 3 proposes a decision-making methodology for an allocating limited monitoring resource to produce an effective water quality monitoring network by
suggesting an index, called station ratio which represents the relationship between the number of monitoring stations and the incremental water quality load within a watershed. In Chapter 4, an allocation methodology for salinity control responsibility is developed in consideration of cost, equity, and their trade-offs among stakeholders. Chapter 5 summarizes the overall conclusion, the major findings, and contributions from the three components, and recommends potential extensions of this research.

LITERATURE CITED


CHAPTER 2
ANALYSIS OF SALINITY SOURCES AND TRANSPORT IN THE UPPER COLORADO RIVER BASIN: MODELING, CALIBRATION, AND UNCERTAINTY CONSIDERATION

ABSTRACT

Salinity in the Upper Colorado River Basin (UCRB) is due to both natural and anthropogenic activities. Given an economic damage of $295 million in 2010 due to salinity, understanding of salinity sources and production together with transport are of great importance. SPARROW is a nonlinear regression water quality model which simulates sources and transport of contaminants such as dissolved-solids. However, SPARROW simulations of dissolved-solids in the UCRB were only available for 1970 through 1998 due to lack of data. More importantly, prior simulations focused on a single year calibration and its transferability to other years, and the validity of this approach is questionable given the changing hydrologic and climatic conditions. This paper, therefore, proposes different calibration approaches to assess the best method to reduce model uncertainty. This study conducted simulations from 1999 to 2011, and the results showed good model accuracy. The dissolved-solids loads at the outlet have been below the representative criteria indicating the effectiveness of ongoing salinity controls. However, the number of monitoring stations decreased significantly recently resulting in higher model uncertainty. The uncertainty analysis was conducted using SPARROW results and bootstrapping. The results suggest that the watershed rankings changed due to

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1 Coauthored by Jongho Keum and Jagath J. Kaluarachchi
the uncertainty analysis indicating that uncertainty consideration should be an important part of the management strategy.

INTRODUCTION

The Colorado River System supplies irrigation, municipal, and industrial water to the western United States and northern Mexico. Salinity in the Colorado River Basin (Figure 2-1) has been a serious concern because of the domestic and international water interests of the riparian states and the two nations (Brownell and Eaton, 1975). The corresponding economic damages due to salinity in the Colorado River Basin especially in the lower basin were estimated at $295 million for 2010 (US Department of the Interior, 2013). The Colorado River is naturally saline due to its geology (Patrick, 2000). The primary geologic material responsible for salinity in the Upper Colorado River Basin (UCRB) is Mancos shale, which is formed from sediments settled at the bottom of the ancient sea that later became parts of the UCRB (Hayes, 1995; Miller et al., 1986; Timothy et al., 1988; Tuttle and Grauch, 2009). Water from precipitation and irrigation dissolves salts in the soils and rocks, and delivers dissolved salts to the stream network. In other words, a combination of natural and anthropogenic processes produces saline water (Watts and Teel, 2003). Therefore, high salinity concentrations and the consequential economic damages on agriculture, municipalities and industries are inevitable. Generally, most salinity contributors are located in the UCRB, due to the distribution of natural geologic materials such as Mancos shale in the region, while the majority of the impaired water users are located in the Lower Colorado River Basin. Therefore, the salinity removal target of the Colorado River is mostly aimed at the
UCRB. The salinity control projects have been implemented since late 1970's by federal agencies, such as US Department of Agriculture (USDA), Bureau of Reclamation (BOR), and Bureau of Land Management (BLM) (US Department of the Interior, 2011).

Many studies have been conducted in the recent years to identify methods to reduce the excessive salinity and the corresponding damage in the Colorado River Basin. The outcomes from these studies can be classified into physical and chemical methods to determine the sources and transport of salts, statistical methods to analyze trends, and salinity prediction modeling. Butler (1996) determined the salinity concentration trends of three existing salinity control programs that consist of irrigated and natural lands for water years 1970 to 1993. Bauch and Spahr (1998) analyzed salinity trends for the main stem of the Colorado River at Cameo, and at a major tributary, the Gunnison River. Generally, salinity in the Colorado River did not show a significant trend during this period (Butler, 1996; Bauch and Spahr, 1998) indicating the previously implemented salinity control units have worked effectively (Anning et al., 2007; Colorado River Basin Salinity Control Forum, 2011).

The statistical model developed by Mueller and Osen (1988) simulates the relationship between streamflow and parameters related to dissolved-solids loads using weighted least-squares regression. However, this model tends to overestimate the dissolved-solids loads (Prairie et al., 2005). Later, Lee et al. (1993) developed and applied a stochastic model combined with mass transport to predict the change in net salt loads and net flow volume due to the changes in agricultural activities in the Colorado River Basin. This model, however, employed assumptions such as steady state and
deterministic flow conditions, and is unable to estimate the hydrologic parameters directly. Nonparametric statistical and stochastic salinity models were developed by others (Prairie et al., 2005; Prairie and Rajagopalan, 2007) to improve previous dissolved-solids simulation models. The major advantage of the nonparametric methods is that no assumption is required to establish the relationship between flow and salt load. These methods are now included in the Colorado River Simulation System (CRSS) by the BOR. The CRSS is a basin-wide long-term planning model based on commercial the software RiverWare™ that supports analysis of river flow and salinity concentration for expected future conditions or operating policies (Colorado River Basin Salinity Control Forum, 2011). However, the CRSS is not able to locate water quality sources or estimate the effects of hydrologic parameters contributing to the transport of contaminants. For better management of salinity at a basin-scale, an understanding of sources and transport is important.

SPARROW (SPAtially Referenced Regressions On Watershed attributes) is a surface water quality model developed by Smith et al. (1997) to demonstrate the in-stream contributions of point sources, nonpoint sources, and transport on total nitrogen and total phosphorus in the conterminous United States. The first application of SPARROW to model salinity, as dissolved-solids, was conducted by Anning et al. (2007) for the southwestern United States. Anning et al. (2007) concluded that about 44 percent of the total salinity load in the southwestern United States is due to natural geology, and that there was a downward trend of dissolved-solids concentration at the outlet of the UCRB. Kenney et al. (2009) extended the work to model salinity sources and transport in
the UCRB for the water year 1991 and this work will hereafter called SPARROW 1991. The year 1991 was selected as a representative year, because the hydrologic and meteorological conditions of this year were near normal (Kenney et al., 2009). SPARROW is typically applied to simulate long-term average conditions (Smith et al., 1997; Alexander et al., 2002; Anning et al., 2007; Hoos and McMahon, 2009), or a single year (Preston and Brakebill, 1999; Kenney et al., 2009). Previous SPARROW calibrations for salinity in the UCRB were conducted from a single year data (Kenney et al., 2009) and median of annual data (Anning et al., 2007). There is a need now to extend this SPARROW modeling effort to understand salinity sources and transport in the recent past, and to identify the effects of salinity control programs that are already in place in the UCRB. In order to meet these needs, Kenney and Buto (2012) extended the SPARROW salinity modeling for the UCRB from 1974 to 1998 using calibration data of SPARROW 1991. However, the work was only extended to 1998 due to lack of data, specifically evapotranspiration (ET). Other limitations of prior modeling studies include the use of single year SPARROW salinity calibration. Therefore, the goal of this work is to extend the prior SPARROW modeling effort to predict the salinity sources and transport in the UCRB for the recent past using the most updated information. The other focus areas will be to determine the best approach for model calibration compared to prior work, to identify the trends of incremental loads from individual watersheds, and to rank watersheds by salinity yields considering model uncertainty. Because there is no dissolved-solids criterion in the UCRB, this work will suggest a representative criterion for dissolved-solids at the outlet of the UCRB.
BACKGROUND

Upper Colorado River Basin

Figure 2-1 shows the physical details of the UCRB which covers parts of five US states; Wyoming, Colorado, Utah, New Mexico, and Arizona. The drainage area is about 280,000 square kilometers (108,000 square miles) with the outlet at Lees Ferry, Arizona. There are 59 8-digit hydrologic unit code (HUC8) watersheds in the UCRB. Water demands in the UCRB are primarily from agriculture consisting of irrigation with a smaller demand from municipal users (Anning et al., 2007). In addition to the natural weathering of local geology, anthropogenic activities, such as irrigation, accelerate dissolution of widespread saline ions in soils or rocks. Colorado’s Grand Valley and Uncompahgre River Basins are considered large contributors to salinity through active irrigation. There are seven major saline springs located in the UCRB as shown in Figure 2-1 (Kenney et al., 2009). The average annual total dissolved-solids load from all seven springs is approximately 800,000 tons/year and typically amount to 10 to 16% of the loading leaving the outlet (US Department of the Interior, 2011).

The major impact of Colorado River salinity is the economic damages on crop production, and municipal and industrial facilities (US Department of the Interior, 2013). It is expected that farmers can earn more profit if salinity impacts are eliminated (Houk et al., 2006). The Colorado River Basin Salinity Control Forum proposed numeric criteria and a plan of implementation to reduce the damages from river salinity (Colorado River Basin Salinity Control Forum, 2011). The proposed dissolved-solids concentration criteria include 723 mg/L below Hoover Dam, 747 mg/L below Parker Dam, and 879
mg/L at Imperial Dam. To achieve these criteria, a number of salinity control units have been installed in the UCRB. Anning et al. (2007) estimated the dissolved-solids concentration decreased with 2.3 mg/L per year from the trend analysis at the outlet of the UCRB from 1974 to 2003. However, these trends can change and rise again without the additional salinity controls (Bauch and Spahr, 1998; Colorado River Basin Salinity Control Forum, 2011). In summary, these observations need to be analyzed within the entire basin to identify the effectiveness of existing salinity control units and to provide decision support in developing future monitoring and control programs in the basin.

**SPARROW Water Quality Model**

SPARROW surface water quality model is a combined statistical and deterministic mass balance model (Schwarz et al., 2006). SPARROW was developed to predict water quality loads from a statistical least square nonlinear regression method using spatially distributed or referenced parameters to identify and quantify the sources of water quality and other factors delivering pollutants. SPARROW is not a forecasting model, but it is able to predict the water quality load distribution based on the sources of origination given the climatic and hydrologic conditions. The model parameters are classified by point and non-point source variables and landscape delivery variables. Conservation of mass is enforced in SPARROW; for example, the load leaving a reach is equal to the sum of salt loads originated within the catchment and the loads entering from the upstream reaches (Schwarz et al., 2006; Kenney et al., 2009). Transport in SPARROW for UCRB is given as
where \( L_i \) is the dissolved-solids load leaving reach \( i \) (kg), \( \hat{L}_j \) is the dissolved-solids load entering from the upstream reaches, \( I(i) \), and delivered to reach \( i \) (kg), \( \delta_i \) is the fraction of load transferred downstream and not affected by diversions (dimensionless), \( S_{n,i} \) is the source \( n \) in reach \( i \) which is the direct load from point sources or area of a geological unit or irrigated lands (kg or km\(^2\) depending on the source and units of corresponding parameter coefficient \( \alpha_n \)), \( \alpha_n \) is the corresponding estimated coefficient for source \( n \) (kg/km\(^2\) or dimensionless depending on units of \( S_{n,i} \)), \( \omega_{n,m} \) is an indicator variable which is 1.0 if the delivery variable \( m \) affects source variable \( n \) and 0.0 otherwise (dimensionless), \( D_{m,i} \) is the landscape delivery variable \( m \) in reach \( i \) such as precipitation, ET, elevation, land cover and soil type which represents the relationship between catchment-wide generated dissolved-solids from source variables and dissolved-solids load at the reach outlet (mm for precipitation or ET, m for elevation, or dimensionless for others), and \( \theta_m \) is the corresponding estimated coefficient for variable \( m \) (Schwarz et al., 2006; Kenney et al., 2009).

Equation (1) in SPARROW requires a hydrologic network of stream reaches and connections. The catchments in SPARROW are delineated using the stream reaches. This work used a stream reach network for UCRB developed by Kenney et al. (2009) which used 1/3 arc-second National Elevation Dataset (NED; US Geological Survey, 2002) and 1:100,000-scale National Hydrography Dataset (NHD; US Geological Survey, 1999) using Geographic Information Systems (GIS). The network consists of 10,679 reaches.
and the corresponding catchments, and 134 dummy reaches with zero catchment areas that are used to better describe confluences.

**METHODOLOGY**

SPARROW consists of sources and landscape delivery parameters. For consistency, this work follows the same parameter classification of SPARROW 1991 by Kenney et al. (2009). Geologic units aggregated into seven groups according to lithology and yield classes, saline springs, and irrigated land area aggregated by lithology groups, are considered as source parameters. Landscape delivery parameters related to soils, meteorology, and geomorphology are; minimum catchment elevation, annual catchment precipitation, ratio between annual catchment precipitation and maximum catchment elevation, annual catchment ET, soil thickness, fraction of catchment area with the selected hydrologic soil characteristic code, and fraction of catchment area covered by forest. The elevation related parameters are applied to irrigated land sources, because elevation affects the irrigation water use (Kenney et al., 2009). Dissolved-solids loads from the saline springs are assumed constant with time. The source parameters, such as areas, and some of the landscape delivery parameters that are related to soil and geomorphology, such as elevation, soil thickness, and soil characteristic code, are time-independent variables. However, precipitation and ET vary temporally. In addition, parameters related to land cover can change gradually as well.

Salinity in the UCRB is measured as dissolved-solids loads or concentrations. Therefore, the term dissolved-solids will be used hereafter to define salinity. The two key assumptions in this work are similar to those of Kenney et al. (2009) and Kenney and
Buto (2012). First, the changes of dissolved-solids loads through reservoir operations are neglected. Second, trans-basin diversions are considered as a fraction of discharge. This diversion ratio is applied to the dissolved-solids loads as well as to the assumption of well-mixed conditions.

Precipitation

Precipitation plays a role in delivering dissolved-solids to streams primarily by dissolving saline ions in soils or rocks as a part of the weathering processes, and the transport of dissolved-solids in surface or ground water to streams. In SPARROW simulations, precipitation is related to landscape delivery parameters such as annual catchment precipitation, and the ratio between annual catchment precipitation and maximum catchment elevation. Precipitation data were available from the PRISM (Parameter-elevation Regressions on Independent Slopes Model) Climate Group (2012). Gridded precipitation data (4 km x 4 km) was converted to catchment scale precipitation for each of 10,679 catchments for each year from 1999 to 2011 using geographic information systems (GIS) tools.

Land Cover

The National Land Cover Database (NLCD) is a product of the Multi-Resolution Land Characterization (MRLC) consortium. The NLCD, updated in 1992, 2001, and 2006, provides 30-meter resolution spatially referenced descriptive data for land surface characteristics (Fry et al., 2011; Homer et al., 2012). Previous studies found that agricultural activities significantly affect the dissolved-solid loads in the UCRB (Iorns et al., 1965; Kenney et al., 2009; US Department of the Interior, 2011). In irrigated lands,
excessive irrigation water expedites dissolution of saline ions from the subsurface by deep percolation (Bethune et al., 2008). Therefore, irrigated lands should be considered as additional dissolved-solids sources, in addition to the natural geologic sources. Land cover type controls transport characteristics of dissolved-solids in SPARROW.

In previous SPARROW modeling efforts, NLCD 1992 was used to determine the fraction of catchment area covered by land cover types together with a dataset from the BOR for determining irrigated agricultural lands (Kenney et al., 2009; Kenney and Buto, 2012). The application of NLCD 1992 was acceptable in the previous studies because there were no available land cover dataset representing 1970’s and 1980’s. However, the continuous application of NLCD 1992 to SPARROW simulations for 2000’s and later is not accurate given the potential land cover changes during the past two decades. In this work, NLCD 2006 is selected to define the land cover types and irrigated lands from 1998 to 2011. According to the NLCD 2006, the most dominant land type is range land followed by forest in the UCRB occupying about 60 and 30% of the basin area, respectively. Agricultural area and urban areas are 2.7 and 0.9%, respectively. The spatial distribution of land cover indicates most areas are natural land and 3.6% of basin area is related to anthropogenic activities. Since the NLCD 2006 is available as a 30-meter gridded dataset, the land cover grids are aggregated and converted to catchment scale using GIS tools.

**Evapotranspiration**

ET is an important hydrologic process and a difficult parameter to measure or predict (Fisher et al., 2005). Previous studies (Kenney et al., 2009; Kenney and Buto,
2012) used a gridded ET dataset estimated by Willmott and Matsuura (2001). Since these ET data were available until 1998, prior SPARROW simulations were conducted until 1998 only. This work used the modified complementary method proposed by Anayah (2012) to estimate ET from readily available meteorological and physical data. This approach is applicable for regional studies where data are limited (Anayah, 2012; Anayah and Kaluarachchi 2013, 2014). In this work, ET for each catchment was predicted using wind speed observations, maximum air temperature, minimum air temperature, and dew point temperature. Spatially distributed temperature data are readily available from the PRISM Climate Group. However, the wind speed dataset is available as station data from the Global Summary of the Day by National Climatic Data Center (NCDC) of National Oceanic and Atmospheric Administration (NOAA). Wind speed point observations were interpolated into grids by kriging. Gridded ET was calculated from wind speed and air temperatures, and scaled to each catchment. The ET estimation procedure using the modified complementary method is given in the Appendix.

*Calculation of Dissolved-Solids Loads*

Liebermann et al. (1987) proposed three types of estimates to represent dissolved-solids concentration of a monitoring station which can be retrieved by WATSTORE of the National Water Information System (NWIS) database of the US Geological Survey (USGS). First, the best estimate is the calculated dissolved-solids which can be calculated from the sum of eight major constituents; calcium, magnesium, sodium, potassium, silica, chloride, sulfate, and carbon expressed as the carbonate equivalent. The second, preferable estimate is the sum of constituents, and the third is the concentrations of
residue on evaporation at 180°C. The preference order was established based on the accuracy of the constituent observations from NWIS (Liebermann et al., 1987). NWIS also provides specific conductance, and Anning et al. (2007) calculated the ratio of dissolved-solids concentration to specific conductance. As a fourth preference, dissolved-solids concentrations were calculated from specific conductance. If the dissolved-solids concentration is calculated, it can be easily converted to the dissolved-solids loads by multiplying with discharge. Liebermann et al. (1987) suggested that logarithmic transformations of dissolved-solids loads and discharge are approximately linear and the distribution of residuals is close to normal and homoscedastic. Three-year moving linear regression coefficients, i.e. slope and intercept, are estimated from discharge observations and the dissolved-solids loads computed from observed dissolved-solids concentrations. The annual dissolved-solids loads are then calculated as the annual sum of daily dissolved-solids loads by substituting daily discharge to the linear relationship between discharge and dissolved-solids load. In this work, dissolved-solids loads were calculated using the NWIS database from 1999 to 2011.

Model Calibration

Since SPARROW is a statistical regression model, model accuracy and prediction reliability depend heavily on the parameters, observations, and calibration method. In the SPARROW salinity model for the UCRB, there are 11 source variables, $S_{n,i}$, which are areas of groups of geological units or irrigated land area, and point sources. Seven landscape delivery variables, $D_{m,i}$, in SPARROW consist of three meteorological parameters related to precipitation and ET, and four soil and geomorphologic parameters
such as land cover, elevation, soil thickness, and hydrologic soil characteristic code. The three meteorological parameters of the $D_{m,i}$ group are time variable given the dependency of local meteorological and hydrologic conditions. In essence, variables such as precipitation and ET vary from year to year. On the other hand, the 11 source variables, $S_{n,i}$, and four soil and geomorphologic parameters among the delivery variables are assumed as time independent because annual variability of land cover and dissolved-solids loading from point sources during the period of analysis is negligible.

Two calibration parameter coefficients, $\alpha$ and $\theta$, influence the salinity response based on the salinity sources of SPARROW. Kenney and Buto (2012) assumed the calibrated $\alpha$ and $\theta$ values from SPARROW 1991 to be constant in time and used this set to simulate salinity in other years. Although Kenney and Buto (2012) verified the adequacy of temporal transferability of SPARROW 1991 to the years 1974 through 1998, the transferability was not assessed for the recent years. If the climatic conditions are different from 1991, then the transferability becomes questionable. Therefore, calibration for each year may be preferred but needs to be further studied. For this purpose, we proposed three calibration options. In method 1, SPARROW is calibrated for each year of simulation using best available information for the given year. In method 2, SPARROW 1991 data are used across all years assuming that these data are representative of hydrology and climatic conditions of other years. However, obvious hydrologic data such as precipitation, ET, other meteorological data will be updated accordingly. Method 3 is similar to the method 2, but the best set of calibrated non-meteorological parameters from method 1 will be used to simulate salinity across all years instead of SPARROW 1991.
data in method 2. The best parameter set from method 1 will be selected based on model accuracy predicted from individual calibrations for all years in method 3.

*Prediction Uncertainty*

With proper model calibration of SPARROW, the contributions from salinity sources and land to water delivery processes can be identified. Using the results of calibrated SPARROW, the incremental salinity yields produced from each watershed can be determined. One of the objectives of this work is to rank the different watersheds for salinity yields for use in future resource allocation of salinity control. Given the uncertainty of model parameters, and therefore model prediction uncertainty, an uncertainty analysis is required to rank the watersheds for salinity yields.

SPARROW uses the resampled bootstrapping method to analyze uncertainty in model prediction. This method generates potential combinations of observations allowing repetitions of observations (Schwarz et al., 2006). Robertson et al. (2009) incorporated uncertainty to rank watersheds for nutrient yields using SPARROW model results when watersheds are ranked based on the confidence limits of ranking score from 200 bootstrap iterations. However, Efron and Tibshirani (1986) recommended 1,000 or more of bootstrap iterations to estimate confidence limits. This work used 1,000 bootstrap iterations for the uncertainty analysis. In addition, the confidence limits of incremental dissolved-solids yields are used to determine watershed ranking contrary to the method of Robertson et al. (2009) to avoid making equal ranking for two or more watersheds.

In order to reduce the dissolved-solids loads at the outlet, it is important to examine the incremental yields (Robertson et al., 2009). Figure 2-2 describes the
proposed watershed ranking method. When 1,000 bootstrap iterations are completed, each watershed has 1,000 different predicted yields. The example in Figure 2-2 assumed normally distributed yields for the two hypothetical watersheds A and B. Comparing the medians only, watershed A yields 100 units while watershed B yields 90 units suggesting that watershed A produces more dissolved-solids than watershed B without considering uncertainty. However, the 90% lower confidence limit of watershed B is higher than that of watershed A. In other words, watershed A is likely to produce 10 units more than watershed B. On the contrary, it can be said that there is only a 10% of probability that watershed A will produce less than 50 units while watershed B will produce less than 65 units with the same probability. Therefore, it can be said that watershed B is likely to yield more dissolved-solids than watershed A at the 90% confidence level. Recalling the management point of view, watershed B has higher priority for salinity management than watershed A, because watershed B will produce more dissolved-solids with equal probability. Using this ranking procedure, the spatial distributions and temporal variations of management priorities are analyzed from of dissolved-solids rankings.

RESULTS AND DISCUSSIONS

Parameter Estimation

Figure 2-3 shows percent differences of annual catchment precipitation compared to the water year 1991, which was proposed as a normal year in the SPARROW 1991 simulations (Kenney et al., 2009). The median, 25th, and 75th percentiles of annual precipitation during 1991 were 30, 22, and 44 cm/year, respectively. These data show that years 2005 and 2010 were relatively wet and 2002 and 2009 were dry years compared to
1991. Figure 2-4 shows the percent differences of ET estimations compared to those made by Willmott and Matsuura (2001) used in the SPARROW 1991 simulation. The ET estimates indicate more water loss due to ET in all years after 1999 compared to 1991. However, a direct comparison between ET in 1991 and other years should be carefully inspected, because the ET data were not from direct observations, but from estimations using different methods. The modified complementary method proposed by Anayah (2012) used in this research tends to be higher than the previous estimation method by Willmott and Matsuura (2001) for the analysis period. The only reason to estimate ET in this work was the lack of observed ET data in the last decade.

In 1975, the Colorado River Basin Salinity Control Forum proposed acceptable salinity criteria to maintain salinity levels at or below those observed in 1972. These criteria were approved by the US Environmental Protection Agency and later adopted by the impacted states. These numeric criteria were established based on flow weighted average annual salinity concentrations in the year 1972 (Colorado River Basin Salinity Control Forum, 1975). Considering the development history of the existing criteria in the Lower Colorado River Basin, it can be assumed that maintaining dissolved-solids concentration at or below levels of 1972 at the outlet of the UCRB may satisfy the criteria for the lower basin. The dissolved-solids concentration at the outlet of the UCRB, Lees Ferry, AZ in 1972, was 566 mg/L, and this concentration is used as the proposed representative dissolved-solids criterion at the outlet of the UCRB in this work (Colorado River Basin Salinity Control Forum, 1975). Figure 2-5 compares the estimated annual dissolved-solids loads from observed data and the proposed criterion. The proposed
criterion as dissolved-solids concentration was converted to dissolved-solids loads using annual discharge measurements. The computed annual dissolved-solids loads at the outlet during the recent decade have remained below the proposed criterion. The dissolved-solids loads remained similar until about 2010 but increased significantly in 2011 with an increase in discharge. During the entire period, however, the dissolved-solids loads have remained below the proposed criterion, so that the existing salinity control programs can be assumed effective.

Evaluation of Model Calibration Methods

As described earlier, the selection of an appropriate calibration method is crucial in SPARROW simulation because some of the delivery parameters are linked to prevailing hydrologic and climatic conditions. The three methods selected for calibration were discussed earlier and these methods were used in SPARROW calibration from 1999 to 2011. Figure 2-6 shows the annual variations of coefficient of determination (R²) values of salinity yield in each year for the three calibration methods, and the number of observations (n) that were used in the calibration. The R² value computed here (also called yield R²) is defined by Schwarz et al. (2006) as

\[
\text{Yield } R^2 = 1 - \frac{\sum_{i=1}^{N} e_i^2}{\sum_{i=1}^{N} \{(f_i^* - \bar{f}^*) - (d_i - \bar{d})\}^2}
\]

where \(e_i\) is the residual at the monitoring station \(i\) in log scale, \(N\) is the number of monitoring stations, \(f_i^*\) is the observed flux at the monitoring station \(i\) in log scale, \(\bar{f}^*\) is the mean observed flux over \(N\) observations, \(d_i\) is the drainage area of the monitoring station \(i\) in log scale, and \(\bar{d}\) is the mean drainage area over \(N\) monitoring stations.
Equation (2) is different from the typical $R^2$ definition by accounting for drainage area. In other words, the denominator of yield $R^2$ equation is from total sum of squares of yields while that of typical $R^2$ equation is from total sum of squares of fluxes. In equation (2), subtraction of drainage area from flux in log space represents yield which is defined by flux per area. Because the dissolved-solids loads are highly correlated with drainage area, a higher value of the typical $R^2$ for flux does not always indicate better model fitness. Therefore, yield $R^2$, which uses the total sum of squares not from flux but from yield as denominator, is a better indicator to determine the adequacy of the SPARROW model (Schwarz et al., 2006).

From the results shown in Figure 2-6, method 1 produced the best yield $R^2$ across all years compared to the other methods and year 2006 produced the highest value. In essence, SPARROW performed statistically best in 2006 among all years and better than other methods. The results from methods 2 and 3 are mixed. In method 3, the calibrated coefficients from year 2006 are used in SPARROW to simulate dissolved-solids loads from 1999 to 2011. It is interesting to compare the results between methods 2 and 3. Method 3 used calibration data from year 2006, which was the best of all years in method 1, while method 2 used calibration data from SPARROW 1991 that were used by Kenney and Buto (2012). The results clearly show that both methods are similar in results between 1999 and 2004 and then method 3 is better between 2004 and 2008. Thereafter the performance of method 3 decreased. As a result, year-to-year calibration (method 1) is better than calibration to a single year and transferring the calibration data to other years. Since the coefficients that describe dissolved-solids sources and transport in
SPARROW are dependent on hydrology and climatic conditions of the basin, the results show that the use of any single year set of calibration data is not suitable for other years. Even though method 3 used the best set of calibration data (of 2006) from all years, the simulations were poor compared to method 1 and yield $R^2$ decreased after 2006 especially in 2011 where the value is less than 0.2.

Furthermore, the dissolved-solids loads are closely related to the geochemical processes as well as physical processes that are sensitive to prevailing environmental conditions. Nezafati et al. (1981) concluded that the controlling factors of dissolved-solids concentration are dilution, particle size fraction, mixing velocity, initial electrical conductivity, and the saturation extract electrical conductivity. Xu and Shao (2002) developed a salt transport model combined with a soil moisture model that considered sorption, dispersion, and sinks. They concluded that saline groundwater plays a major role in soil salinity because salinity distribution has a close relationship with water table depth. These finer processes are difficult to simulate at basin scale for management purposes. Influences of geochemical and transport processes that are not explicitly modeled in the basin scale SPARROW model, are considered by lumped or surrogate parameters, such as areal extent of geologic units and land cover. As a result, year-to-year calibration, as described in method 1, is recommended to describe dissolved-solids sources and transport for a given year. Therefore, simulation results will be presented using the calibration method 1 hereafter.

**Simulated SPARROW Results**

Model residuals of the SPARROW nonlinear least squares regression model
should be independent and identically distributed. The normal distribution of residuals is not necessarily required for validating SPARROW, because the estimate used in SPARROW is consistent regardless of the residual distribution (Schwarz et al., 2006). Figure 2-7 shows plots for evaluating model errors from SPARROW simulations from 1999 to 2011 using the calibration method 1. The predicted versus observed loads are close to 45 degree line and unbiased, such that the model is systematically and structurally not correlated indicating independence of residuals. The residuals versus predicted loads and yields show common spreads resulting in the validity of the simulations. Even though the normality of residuals is not a precondition of residuals for the SPARROW model, the residuals from simulations in this research are close to a normal distribution. Therefore, calibration of SPARROW using calibration method 1 is valid. The annual variation of total incremental yields across all catchments is shown in Figure 2-8. Dissolved-solids loads from saline springs are excluded in Figure 2-8. The UCRB, the median, and 25th and 75th percentiles are shown. When comparing annual total dissolved-solids loads in Figure 2-5 with yield results of Figure 2-8, it is clear that the total incremental yields and dissolved-solids loads at the outlet have strong correlation. Although not shown here, the correlation coefficient between annual discharge and total dissolved-solids loads at the outlet is estimated at 0.80. The total incremental yields are high in 1999 through 2001 and a similar behavior is shown by the total dissolved-solid loads at the outlet.

The confidence intervals of total incremental yields from 2005 to 2011 are wider than those of early 2000’s. One possible reason for this wider distribution is the number
of monitoring stations. Figure 2-6 shows the available number of observations, where it is seen that there is a gradual decrease during this period. A nonlinear regression model such as SPARROW is heavily dependent on the number of observations for model accuracy. Although Figure 2-7 shows good model fit across all simulated years, model accuracy of each year can vary. An increase in model uncertainty, as seen in Figure 2-8, could be caused by a reduction in monitoring stations over time. The total annual incremental yields are estimated close to or below the SPARROW 1991 results except from 1999 to 2001 and 2008.

SPARROW results provide incremental yields for each catchment, land use type, and geologic material, allowing the distribution of total dissolved-solids loads from irrigation at the outlet to be calculated from bootstrapping simulations. Figure 2-9 shows the results for few select years. On average, the contribution of irrigation to river salinity is around 40% from 1999 to 2011. The results show that the percentage of dissolved-solids loads from irrigated lands at the outlet of the UCRB is mostly mixed with a slight increasing trend after 2004, even though the irrigated land area is constant by NLCD 2006. A more important observation is that the uncertainty distribution within each year increases with time. It is also important to note that the percentage of irrigated land during the past three decades remained around 3% indicating that there is no significant change according to NLCDs (Fry et al., 2011; Homer et al., 2012). In addition, total dissolved-solids loads at the outlet as well as the total incremental yields across all catchments have remained relatively constant since early 2000. Therefore, this small increasing trend of percent contribution from irrigation may be mostly due to the
increased uncertainty of the SPARROW results with decreasing number of monitoring stations across the UCRB as shown in Figure 2-6. The number of monitoring stations decreased 70% from 218 in 1991 to 66 in 2011.

The uncertainty analysis presented earlier was used to address management issues. The six highest dissolved-solids yielding watersheds from all sources among the 59 HUC8 watersheds in the UCRB for 1991, 2001, and 2011, are shown in Table 2-1. The results of 1991 are from Kenney et al. (2009). First, the ranking of watersheds have changed due to the incorporation of uncertainty. Only one watershed of the highest six yielding watersheds from 1991 remained in the same rank after considering uncertainty. Similarly, only one watershed, HUC8 14030003, San Miguel, Colorado, remained in the top six in 2001, and only watershed 14010002, Blue, Colorado, remained in 2011. Also HUC8 14010003, Eagle, Colorado, was the highest yielding without uncertainty in 2011 and this watershed became the 11th with uncertainty. The highest yielding watersheds for 1991 and 2011 are the same in both years and the watershed HUC8 14080102, Piedra, Colorado, ranked second in 2001. However, the highest yielding watershed for 2001, HUC8 14030003, San Miguel, Colorado, is not in the top 6 in 1991 or 2011. Although SPARROW with its calibrated parameters can be used to estimate mean incremental yields, the uncertainty analysis is a priority to meaningfully understand the distribution of highest yielding watersheds in the UCRB. From a management perspective, limited resources need to be allocated based on the potential to maximize salinity control. Accordingly, watersheds with potential for producing large incremental yields need to be identified for resource allocation. The proposed uncertainty analysis not only showed the
importance of incorporating uncertainty in the analysis but also identified the high priority watersheds needing salinity control measures.

Figure 2-10 shows the spatial and temporal distributions of rankings of total incremental yields at 10-year intervals; 1991, 2001, and 2011. The available monitoring stations changed with time and these changes may affect the ranking. Similar to other regional studies, this effect was neglected and the best available data were used in this work. When the ten highest yielding watersheds are considered in each year, four of these ten watersheds in 1991 remained in the top ten in 2001, and 2 of these remained until 2011. Similarly, four watersheds are shown as high yielding watersheds in 2001 and 2011. The two watersheds that remained in the top ten are HUC8 14010002 Blue Watershed and HUC8 14080102 Piedra Watershed. There are three salinity control units that were installed by USDA between 1991 and 2011; Mancos Valley Unit in 2005, Silt Unit in 2006, and Manila-Washam Unit in 2007 (US Department of the Interior, 2011). Mancos Valley Unit is located in HUC8 14080107 Mancos Watershed which is ranked in the 50’s out of 59 HUC8 watersheds. Silt Unit is located in HUC8 14010005 Colorado Headwaters-Plateau Watershed which is ranked between 10 and 20. It should also be noted that the rank is one of many other factors in selecting a location for salinity control. Effectiveness and costs of salinity reduction can be other competing factors in the decision-making. The agricultural activities in the UCRB are highly concentrated in HUC8 14010005 Watershed which includes Silt Unit, indicating that these watersheds require more aggressive salinity control measures. On the other hand, the ranking of Manila-Washam Unit located in HUC8 14040106 Upper Green-Flaming Gorge Reservoir
Watershed changes from 20’s to 40’s between 2001 and 2011. These results suggest that the salinity control units installed here are working well and the incremental dissolved-solids yields from the watersheds are reducing. Generally, regions near the Gunnison River Basin located in the western of Colorado, and San Juan River Basin near the border between Colorado and New Mexico produce higher dissolved-solids than other watersheds. According to the land cover dataset, agricultural lands are primarily located in those regions, and therefore the corresponding high loadings are no surprise. These results also confirm that irrigation activities have accelerated salinity generation in the UCRB.

SUMMARY AND CONCLUSIONS

SPARROW is a nonlinear regression water quality model capable of simulating regional scale dissolved-solids sources and transport. Prior works related to predicting dissolved-solids using SPARROW in the UCRB are only available until 1998 due to lack of forcing data especially evapotranspiration. Given the impacts of salinity to the Lower Colorado River Basin, the need to identify the salinity sources, transport, and trends spatially and temporally is important at the present time. Previous work showed limitations in the calibration approach, where a single year calibration parameter set was used in other years too. Given the sensitivity of hydrologic and climatic conditions to transport of dissolved-solids, this approach of transferability to other years may not be valid. The purpose of this work is therefore to update the existing information and data and revise the calibration approach to simulate dissolved-solids sources and transport in the UCRB for the past decade or more. Additional goals include using an uncertainty
analysis to rank and identify the vulnerable watersheds for salinity controls for limited resource allocation.

The modified complementary method was used to estimate ET (Anayah, 2012; Anayah and Kaluarachchi, 2013, 2014) using readily available temperature and wind speed data. Land cover and irrigated land areas were updated using NLCD 2006 together with updated precipitation data and dissolved-solids observations to calibrate SPARROW. The trends of dissolved-solids loads with discharge observations at the outlet of the UCRB showed good correlation, and the predicted incremental yield of each watershed showed similar trends. Since the dissolved-solids criteria of the Colorado River Basin are established for the lower basin only, a representative criterion at the outlet of the UCRB was suggested. When compared to this criterion, the total dissolved-solids appearing at the outlet were near or below the suggested criterion indicating effectiveness of the ongoing salinity control measures. SPARROW simulations were conducted using the three calibration methods. This study concluded that the calibration method 1, which is individual year calibration, is the best because accuracy of the simulated results from 1999 to 2011 shows good results based on yield $R^2$ proposed for SPARROW.

The uncertainty analysis and the ranking scheme proposed earlier were implemented here using the results of SPARROW. The purpose is to identify the watersheds producing high incremental yields of dissolved-solids such that appropriate salinity control measures can be proposed. The uncertainty analysis was conducted using 1,000 iterations of resampled with bootstrapping. The lower confidence limits of the incremental dissolved-solids yields from the bootstrapping were estimated, because these
lower confidence limits represent the statistically significant minimum amounts of dissolved-solids to be expected from a watershed. The information from this analysis showed that model uncertainty plays an important role in identifying the vulnerable watersheds. Neglecting model uncertainty in SPARROW modeling and the use of deterministic results can provide misleading information related to watershed ranking.

The number of monitoring stations available in the UCRB decreased during the recent years with 218 stations in 1991, 49 stations in 2007 and 2008, and 66 stations in 2011. Although model results from SPARROW showed good accuracy across all years, there may be less accurate results in some of the years due to increasing model uncertainty. This possibility is shown in the wider distribution of uncertainty in the form of confidence interval in the predicted total incremental yield of dissolved-solids with time. As a result, SPARROW simulations showed that additional monitoring stations may be required to reduce uncertainty such that management decision can be made reliably.
APPENDIX

*Modified Complementary Method*

The modified complementary method predicts actual evapotranspiration (ET) from land surface (Anayah, 2012). The equation for estimated ET (mm/day) is

\[ \text{ET} = \frac{2G_1}{G_1 + 1} \text{ETW} \]  

(3)

where \( G_1 \) is the relative evaporation that occurs under similar wind and humidity conditions from a saturated surface as its actual temperature, and ETW is the wet environment ET (mm/day).

First, \( G_1 \) is defined by Equation (4), and the relative drying power, D, is given in Equation (5).

\[ G_1 = \frac{1}{c_1 + c_2 \exp(c_3 D)} \]  

(4)

\[ D = \frac{E_a}{E_a + (R_n - G_{\text{soil}})} \]  

(5)

where \( c_1 = 1.0, c_2 = 0.028, \) and \( c_3 = 8.045, \) respectively, \( E_a \) is the drying power of air (mm/day), \( R_n \) is the net radiation (mm/day), and \( G_{\text{soil}} \) is the soil heat flux (mm/day) which can be neglected for annual periods because it is relatively small compared to net radiation.

The drying power of air, \( E_a \), is estimated from vapor pressure and wind speed as

\[ E_a = 0.35 (\beta + 0.54U) [(e_s - e_a) \times a_1] \]  

(6)

where \( \beta \) is constant at 1.0, \( U \) is the wind speed at 2m above ground surface (m/s), \( e_s \) is the saturated vapor pressure at temperature, \( T \) (mbar), \( e_a \) is vapor pressure of air (mbar), and \( a_1 \) is the unit conversion factor (=0.75 mmHg/mbar). Vapor pressures \( e_s \) and \( e_a \) can be
expressed using $T$ and dew point temperature, $T_d$ (Anayah, 2012).

Next, ETW in Equation (3) is estimated from net radiation and soil heat flux as follows:

$$ETW = \alpha \frac{\Delta}{\gamma + \Delta} (R_n - G_{soil})$$

(7)

where $\alpha$ is a constant of 1.28, $\Delta$ is a rate of change of saturation vapor pressure with temperature, and $\gamma$ is psychrometric constant of 0.066 kPa/K (Dingman, 2002).

Since direct observations of radiation are limited, radiation values are calculated using the procedure given in American Society of Civil Engineers (ASCE) (2005). Net radiation is the net amount of radiation to evaporate water from the ground or plant surfaces, and is obtained from the differences between incoming and outgoing energy.

$$R_n = R_{ns} - R_{nl}$$

(8)

where $R_{ns}$ is the net solar, i.e. incoming and short wave, radiation (MJ/m$^2$day), and $R_{nl}$ is the net terrestrial, i.e. outgoing and long wave, radiation (MJ/m$^2$day). The net solar radiation is given by the differences between incoming and reflected radiation;

$$R_{ns} = (1 - \alpha)R_s$$

(9)

where $\alpha$ is albedo at 0.23 (ASCE, 2005), and $R_s$ is incoming solar radiation (MJ/m$^2$day). ASCE (2005) suggested three equations to estimate solar radiation from observed sunshine hours, measured from a nearby weather station, or air temperature. Air temperature is being observed continuously from various locations, while actual sunshine hours are not. In addition, there are not enough weather stations which measure solar radiation in the UCRB. Therefore, net radiation is estimated from the air temperature, and the equation developed by Hargreaves and Samani (1982) given as
\[ R_s = k_{R_s} \sqrt{(T_{\text{max}} - T_{\text{min}})} \, R_a \]  

(10)

where \( k_{R_s} \) is the adjustment coefficient which varies from 0.16 (for interior locations used in this work) to 0.19 (for coastal locations), \( T_{\text{max}} \) is the maximum air temperature \( (^{\circ}\text{C}) \), \( T_{\text{min}} \) is the minimum air temperature \( (^{\circ}\text{C}) \), and \( R_a \) is the extraterrestrial radiation \( \text{MJ/m}^2\text{day} \) which is given as

\[ R_a = \frac{24}{\pi} G_{sc} d_r (\omega_s \sin \phi \sin \delta + \cos \phi \cos \delta \sin \omega_s) \]  

(11)

where \( G_{sc} \) is the solar constant at 4.92MJ/m²h, \( d_r \) is the inverse relative distance factor for the earth and sun (dimensionless), \( \omega_s \) is the sunset hour angle (radians), \( \phi \) is the latitude of the location (radians), and \( \delta \) is the solar declination (radians). The \( d_r \) and \( \delta \) are calculated as

\[ d_r = 1 + 0.033 \cos \left( \frac{2\pi}{365} J \right) \]  

(12)

\[ \delta = 0.409 \sin \left( \frac{2\pi}{365} J - 1.39 \right) \]  

(13)

where \( J \) is the number of the day in the year.

The net long wave radiation can be calculated by

\[ R_{nl} = \sigma f_{cd}(0.34 - 0.14\sqrt{e_a}) \left[ \frac{T_{K,\text{max}}^4 + T_{K,\text{min}}^4}{2} \right] \]  

(14)

where \( \sigma \) is the Stefan-Boltzmann constant at 4.901 \times 10^{-9} \text{ MJ/K}^4\text{m}^2\text{day} \), \( f_{cd} \) is the cloudiness function (dimensionless, \( 0.05 \leq f_{cd} \leq 1.0 \)), \( e_a \) is the actual vapor pressure (kPa), \( T_{K,\text{max}}^4 \) is the maximum absolute temperature during the 24-hour period (K), and \( T_{K,\text{min}}^4 \) is the minimum absolute temperature during the 24-hour period (K). The cloudiness function value, \( f_{cd} \), is calculated as
\[ f_{cd} = 1.35 \frac{R_s}{R_{so}} - 0.35 \]  

(15)

where \( R_s \) is the measured or calculated solar radiation (MJ/m² day), \( R_{so} \) is the calculated clear sky radiation (MJ/m² day), and the ratio between these two radiations becomes the relative solar radiation which ranges from 0.3 to 1.0 according to the variation of \( f_{cd} \). The \( R_{so} \) can be calculated as

\[ R_{so} = (a_s + b_s) R_a \]  

(16)

where \( a_s \) is a constant representing the fraction of the extraterrestrial radiation reaching the earth surface on completely overcast days, and \( b_s \) is a constant representing the additional fraction on clear days. The values of these constants are recommended as 0.25 and 0.50, respectively, according to ASCE (2005).

LITERATURE CITED


American Society of Civil Engineers (ASCE), 2005. The ASCE Standardized Reference Evapotranspiration Equation. Environmental and Water Resources Institute of the ASCE.


Standards for Salinity Colorado River System.


(SPARROW) and Regional Classification Frameworks. Hydrological Processes 23:2275-2294.


PRISM Climate Group. Digital Climate Data: Precipitation, Average Maximum Temperature, Average Minimum Temperature, and Dew Point Temperature.


Table 2-1. The highest six dissolved-solids yielding HUC8 watersheds at 10-year intervals. The watersheds in bold indicate the watersheds remaining in the top six in the same year after incorporating uncertainty.

<table>
<thead>
<tr>
<th>Rank</th>
<th>1991</th>
<th>2001</th>
<th>2011</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>without uncertainty</td>
<td>with uncertainty</td>
<td>without uncertainty</td>
</tr>
<tr>
<td>1</td>
<td>14010003</td>
<td><strong>14080102</strong></td>
<td>14060002</td>
</tr>
<tr>
<td>2</td>
<td>14010001</td>
<td>14050005</td>
<td>14040104</td>
</tr>
<tr>
<td>3</td>
<td>14040106</td>
<td>14080103</td>
<td>14050002</td>
</tr>
<tr>
<td>4</td>
<td><strong>14080102</strong></td>
<td>14010004</td>
<td><strong>14030003</strong></td>
</tr>
<tr>
<td>5</td>
<td>14030003</td>
<td>14050004</td>
<td>14030001</td>
</tr>
<tr>
<td>6</td>
<td>14010002</td>
<td>14030002</td>
<td>14050001</td>
</tr>
</tbody>
</table>
Figure 2-1. Physical layout of the UCRB and the Lower Colorado River Basin (LCRB) in the Colorado River System and the larger map showing the details of the UCRB.
Figure 2-2. Hypothetical diagram illustrating the proposed uncertainty analysis and corresponding ranking of watersheds.
Figure 2-3. Percentage differences of annual precipitation of the UCRB catchments compared to 1991.
Figure 2-4. Percentage differences of annual ET of the UCRB catchments compared to 1991.
Figure 2-5. Estimated dissolved-solids loads leaving the outlet at Lees Ferry, Arizona compared to the proposed criterion given as dissolved-solids concentration and converted to dissolved-solids loads by annual discharge.
Figure 2-6. Annual variation of yield R2 produced by the three calibration methods and the number of monitoring stations.
Figure 2-7. Diagnostic plots for SPARROW model fit using calibration method 1 for the analysis period of 1999 to 2011: (a) predicted and observed loads, (b) quantile-quantile plot of residuals, (c) residuals and predicted load, and (d) residuals and predicted yield.
Figure 2-8. Annual variations of total incremental yields of the UCRB using calibration method 1 compared to the results of SPARROW 1991 excluding the loads from saline springs.
Figure 2-9. Predicted percentage of total dissolved-solids loads produced from irrigated lands and leaving from the outlet, Lees Ferry, Arizona. The data is from calibration method 1 and includes loading from saline springs. The boxes are showing interquartile ranges with medians at notches. Whiskers are showing the most extreme values that are not outliers, and were drawn with maximum whisker length of 1.5. Data of 1991 is from SPARROW 1991 (Kenney et al., 2009).
Figure 2-10. Watershed ranking for incremental dissolved-solids yields with uncertainty from calibration method 1 (a) 1991, (b) 2001, and (c) 2011. Note A is 14010002, B is
14010003, C is 14010005, D is 14030003, E is 14040106, F is 14080102, and G is 14080107.
CHAPTER 3

A DECISION-MAKING METHODOLOGY FOR AN EFFECTIVE WATER QUALITY MONITORING NETWORK

ABSTRACT

The number of water quality monitoring stations has been decreasing in the US during the past few decades. Scarcity of observations can easily produce model uncertainty due to unreliable model calibration. An effective hydrometric network is important not only for model calibration, but also for resources management. Redundant or improperly located monitoring stations may result in increasing monitoring costs without improving the understanding of water quality behavior. In this work, a methodology is proposed to predict the adequate number of monitoring stations and their locations at HUC8 scale for a target monitoring requirement. The proposed methodology is demonstrated for the Upper Colorado River Basin (UCRB) where salinity is a serious concern. The level of monitoring is defined by an index called, station ratio (SR), which represents the relationship between the number of monitoring stations and the incremental water quality load within a watershed. The number of stations required in each watershed was proposed using the target SR, based on the actual SR of the existing water quality monitoring network. If monitoring stations are primarily located in low salinity producing watersheds, the average actual SR tends to increase, and vice versa. Results indicate that the spatial distribution of the recent water quality monitoring network of UCRB in 2011 is focused on low salinity producing watersheds, such that

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2 Coauthored by Jongho Keum and Jagath J. Kaluarachchi
additional monitoring efforts are required in other watersheds. The proposed methodology and the results of this work show that SR is a simple and a practical indicator of monitoring redundancy and/or needs in a large basin such as the UCRB when planning and management of resources are needed.

INTRODUCTION

Hydrometry includes all aspects of water-related measurements providing information, such as water levels, shape and level of waterways, surface water and ground water discharge, water quality, etc. (Herschy, 1999; Boiten, 2000; Mishra and Coulibaly, 2009). In most cases, because one measurement in a location cannot represent all the information of an area, a hydrometric network, defined as a combined system of spatially and temporally distributed information, is required. The primary purpose of gathering information from a hydrometric network is to conduct an appropriate statistical analysis to answer specific questions (Moss, 1979) where the ultimate goal is to support decision-making. Gathering more data may be considered the best strategy to improve hydrologic information, but in some cases, combining inadequate or redundant data can worsen monitoring quality of hydrometric networks (Davis et al., 1979; Langbein, 1979). In addition, hydrometric networks require capital and manpower investments for installation, maintenance, operation of monitoring stations, and sample collections. Therefore, within a limited financial budget and human resources, finding the optimal number and the locations of monitoring stations is important for hydrometric network design (Moss, 1979; Husain, 1989).

The World Meteorological Organization (WMO, 1965) categorized monitoring
stations into principal, secondary, and special stations. The secondary stations are operated intermittently for establishing correlation or for complementary purposes. Special stations are installed only for special cases where specific information is needed. However, principal stations are the most important stations for statistical analyses, and should be maintained continuously. The principal stations define the minimum size of a hydrometric network. Therefore, it is recommended that analyses to find the optimum network should be applied only after the minimum network has been established (WMO, 1965).

There are numerous methods to design hydrometric networks. Mishra and Coulibaly (2009) summarized network design approaches, incorporating statistical analysis, spatial interpolation, entropy, optimization, basin physiographic characteristics, sampling strategies, etc. In general, the design of a hydrometric network faces difficulties due to the lack of understanding about how to establish the objective measures (Harmancioglu and Alpaslan, 1992). In addition, most methods are applied to observe precipitation and streamflow, and these methods are sometimes difficult to apply to water quality monitoring networks. For example, spatial interpolation is not applicable to monitor streamflow or water quality. Strobl and Robillard (2008) provided a review of previous research studies that indicated a versatile methodology for water quality network design does not exist.

Most statistical approaches have targeted how to reduce the errors from monitoring networks to group the networks. Harmancioglu and Alpaslan (1992) applied an entropy-based method to assess an existing water quality monitoring network, and
quantify the benefits from the enhanced network. Entropy in the network design addresses an uncertainty measure of hydrologic information, and was used to assess the efficiency and cost-effectiveness of the existing network. Ammar et al. (2008 and 2011) developed a methodology using a Bayesian framework with relevance vector machines to analyze a groundwater quality monitoring network. Strobl et al. (2006) developed a critical sampling point methodology to design water quality monitoring networks for small agricultural or forested watersheds by using a total phosphorus simulation model. Because the sources and transport of total phosphorus are closely related to the interactions between land use, topography, hydrology, vegetation, and soil, a normalized index, called the potential stream pollution index, was used to evaluate and prioritize target regions. Moss and Gilroy (1980) and Gilroy and Moss (1981) developed cost effective streamgauging strategies, and applied these to the Lower Colorado River Basin. The objective was to allocate resources to reduce uncertainties at monitoring stations, which is a function of visiting frequencies.

In order to manage the salinity issues in the Colorado River Basin, a number of studies have been conducted. SPARROW (SPAtially Referenced Regressions On Watershed attributes) surface water quality model developed by Schwarz et al. (2006) was used to simulate salinity generation in the Upper Colorado River Basin (UCRB) (Anning et al., 2007; Kenney et al., 2009; Kenney and Buto, 2012; Kenney et al., 2012; see Chapter 2). After the initial salinity analysis in the western United States by Anning et al. (2007), Kenney et al. (2009) focused on the UCRB and simulated for water year 1991 which was defined as a hydrological normal year. Kenney and Buto (2012) and Kenney
et al. (2012) extended the SPARROW salinity model for the UCRB to simulate salinity up to 1998 but not any further due to lack of data, specifically evapotranspiration. The recent work by Keum and Kaluarachchi (see Chapter 2) extended SPARROW modeling to 2011, and they identified the need for better data gathering for improved model calibration and verification. The results also identified the increasing uncertainty due to the decreasing availability of the number of monitoring stations and corresponding data.

The goal of this work is to develop a decision-making methodology for an effective water quality monitoring network to gather essential data for improved modeling. For this purpose, spatially referenced salinity data in the UCRB will be used with the assistance of the water quality model SPARROW (see Chapter 2). The methodology will discuss the opportunities to identify the number and approximate locations of the monitoring stations; therefore, the redundancies and scarcities of the existing water quality monitoring network can be assessed. In addition, the relationship between the number of monitoring stations and the uncertainty of the SPARROW model will be estimated as well. The major contribution of this research is to provide a practical framework to estimate priorities for the monitoring stations, so that decision-makers can use these priorities to develop and maintain monitoring stations within available resources.

METHODOLOGY

Description of Salinity Monitoring in the UCRB

Monitoring networks in the United States have been shrinking significantly during the recent decades due to financial limitations (USGS, 1999; Anning et al., 2007; Chapter
2). USGS (1999) estimated 33 to 43% of funds for monitoring networks in the United States have been eliminated, and these budget cuts resulted in a significant loss of monitoring stations or fewer sampling visits. Figure 3-1 shows the decrease in the numbers of monitoring stations in the UCRB at which the total dissolved-solids (TDS) concentrations were measured during the last two decades. There were 218 available stations used in the SPARROW simulation in 1991; however, this number decreased 70% to around 50 after 2006. This decreasing trend may cause an increase of uncertainty in model predictions (see Chapter 2). Figure 3-2 shows the currently active monitoring stations which observe both TDS and discharge (65 stations in 2011), active streamgauging stations (169 stations), streamgauging stations including non-active stations (426 stations), and the predicted TDS loads using the SPARROW model. Consideration for more monitoring efforts should be typically made in areas that produce large amounts of contaminants. Unfortunately the spatial distribution of current monitoring stations and the corresponding large salinity producing areas do not coincide with each other in the UCRB, indicating that the monitoring network needs to be upgraded by identifying additional monitoring needs and redundancies.

*Station Ratio*

WMO (1965) suggested a minimum density of precipitation and streamflow monitoring station network for different types of regions by defining a coverage area per station; for example, 1,500-10,000 km\(^2\) per precipitation station for arid and polar zones. However, this type of index may not be appropriate for water quality observation, because water quality can vary significantly due to precipitation, land cover, geology,
point sources, etc. Therefore, the station ratio (SR) is proposed in this work and defined as

$$SR = \frac{N}{M}$$  \hspace{1cm} (1)

where N is the number of water quality monitoring stations within an area and M is water quality load (units of mass per unit time) produced in the given area. SR is a number that can use any units of mass that are convenient to the users. In this work, million tons per year will be used to describe the TDS load such that the unit of SR is the number of monitoring stations per million tons of TDS per year. SR is more meaningful than the area per station method used by WMO for water quality monitoring, because mass, M, is the ultimate product of water quality related parameters including areal effects.

*Scenario Development*

Similar to most other studies about the optimal monitoring locations, the methodology proposed in this work determines the reduction of monitoring from a given network (Mooley and Ismail, 1981; Dymond, 1982; Husain, 1989; Harmancioglu and Alpaslan, 1992; Spence et al., 2007). The potential to reduce monitoring stations from the network of 65 stations in 2011 is not practical because the existing number of stations is relatively small, and only scenarios which will produce more monitoring stations than the current network are considered. This work proposes the selection of tentative monitoring stations consisting of two scenarios. In scenario 1, all active stream gauges near and around the outlet of a catchment are considered. It should be noted that these active stations monitor current streamflows but may not be monitoring salinity. In scenario 2, all active monitoring stations used in the scenario 1 and all inactive monitoring stations in
and around the outlet of a catchment (i.e., no current monitoring for both streamflow and salinity) are considered. There are 1,143 current monitoring stations in the UCRB installed by USGS. Among the 1,143 stations, 169 stations meet the criteria of scenario 1, and 426 stations conform to criteria of scenario 2. Accordingly, these are the maximum number of the monitoring stations possible for each scenario. The spatial distributions of the monitoring stations for both scenarios are shown in Figure 3-3. The monitoring stations are located primarily in the mountainous regions of Colorado and northeastern Utah, while only a few stations are installed in the northern and southwestern regions of the UCRB.

Selective Monitoring Stations

Since SR is formulated from the relationship between the number of monitoring stations and water quality loads, the number of monitoring stations to be operated varies with changes in SR. Accordingly,

\[ N_{SR,i} = SR_s \times M_i \]  

(2)

where \( N_{SR,i} \) is the number of monitoring stations from a target SR in watershed i, \( SR_s \) is the given target SR in a scenario, and \( M_i \) is water quality loads (million tons of TDS per year). This relationship is a transposition of equation (1), representing the target number of monitoring stations with a given SR for a specific scenario. Then, the optimal number of monitoring stations can be estimated by comparison to \( N_{SR,i} \) with the total number of available monitoring stations.

\[ N_i = \min(N_{max,i}, N_{SR,i}) \]  

(3)

where \( N_i \) is the applicable number of monitoring stations in watershed i, and \( N_{max,i} \) is the
total number of available monitoring stations in watershed i for each scenario. Several groups of \( N_i \) for all watersheds, according to each given SR, will be estimated to determine the watershed-based spatial distribution of the number of monitoring stations, and will be used to make decisions as to whether stations are redundant or scarce.

Hydrologic units were introduced by USGS (1975) and Seaber et al. (1987) to manage water resources effectively. The hydrologic units include watershed delineations, codes, and names. There are four levels of hydrologic units, such as regions (2-digit code), subregions (4-digit code), basins (6-digit code), and subbasins (8-digit code). The levels have been extended to six levels by adding watersheds (10-digit code) and subwatersheds (12-digit). Considering the variation of the number of monitoring stations during the past two decades is from 38 to 218, 59 HUC8 (8-digit hydrologic unit codes) watersheds in the UCRB are acceptable as the watershed size for this work.

**Water Quality Loads**

Water quality loads, \( M_i \), are required to calculate the number of monitoring stations from a given SR in each watershed, \( N_{SR,i} \), using equation (2). For the watersheds where monitoring stations have been installed, observed water quality loads can be used. The National Water Information System (NWIS) database of the USGS provides observations of salinity concentration and daily discharge which are related to the salt load calculation. Liebermann et al. (1987) proposed the calculated dissolved-solids, the sum of constituents, the concentration of residue on evaporation, and the specific conductance as salinity concentration from the NWIS database. After the calculation of salinity concentration, salt load can be estimated by multiplying concentration and
discharge. Anning et al. (2007) and Keum and Kaluarachchi (see Chapter 2) estimated the salt loads in the UCRB from 1974 to 2003 and from 1998 to 2011, respectively. Because the year 2011 was selected to represent the current condition, and year 2002 and 2004 were selected to analyze temporal variation, Salt loads estimated by Keum and Kaluarachchi (see Chapter 2) are used in this work. Predicted loads are used where observed loads are not available.

The SPARROW surface water quality model is a hybrid model which employs a statistical nonlinear least squares regression method with inputs from spatially distributed deterministic parameters to quantify the effects of parameters on in-stream contamination (Schwarz et al., 2006). The model parameters are divided into two categories; (1) source variables including point sources or land areas which are dependent on parameters such as land covers and geology, and (2) landscape delivery variables which represent changes and transportation from a location of pollutant release to the catchment outlet. SPARROW is a mass balance model where the load at the outlet of a catchment is equal to the sum of loads released in the catchment and delivered from the directly connected upstream catchments (Schwarz et al., 2006; Kenney et al., 2009; Chapter 2). The SPARROW model was applied to predict salinity in the Colorado River Basin as a part of the southwestern United States (Anning et al., 2007). Kenney et al. (2009) and Kenney and Buto (2012) extended the SPARROW application in the UCRB until 1998 due to the lack of data. In Chapter 2, Keum and Kaluarachchi proposed alternative data gathering methods for SPARROW in the UCRB using readily available climatic data. In this work, the most recent salt load predictions for 2011 estimated by Keum and Kaluarachchi
(Chapter 2) were used to represent the current conditions.

RESULTS AND DISCUSSIONS

Station Ratio

As described earlier, the number of monitoring stations which are active for both streamgauging and salinity measurements are 64 in 2011. Keum and Kaluarachchi (2014) estimated the total salt loads from the UCRB as 8.5 million tons per year in 2011. Therefore, the lumped SR using the total salt loads and the total number of monitoring stations in the entire UCRB is estimated to be 7.5 using equation (1). However, the average SR among 59 HUC8 watersheds using the incremental salt loads and the number of monitoring stations from each watershed is 14.7. The difference between the lumped SR and the average SR indicates that the hydrometric network in 2011 is not perfect. The term effectiveness is used here to represent an equitable distribution in the context of similar SR values among watersheds. If monitoring stations are dominantly located in the high salinity producing watersheds compared to the low salinity producing watersheds, the average actual SR will decrease, while average actual SR will increase if monitoring stations are predominantly located in low salinity producing watersheds. The actual SRs of individual watersheds vary from zero to 115 in 2011. A SR of zero means that there is no single monitoring station in a particular watershed. Twenty four watersheds among 59 watersheds in the UCRB do not have stations for salinity monitoring in 2011 and have SRs of zero accordingly.

The maximum number of monitoring station inventories of scenarios 1 and 2 are 169 and 429 stations, respectively. Therefore, the corresponding lumped and average SRs
are 19.9 and 27.6 for scenario 1, and 50.1 and 68.2 for scenario 2, respectively. For both scenarios, the average SRs are greater than the lumped SRs, indicating monitoring stations from both scenarios are relatively concentrated in the low salinity producing watersheds similar for the current condition in 2011. Figure 3-3 shows the distributions of actual SR compared to the lumped SR of each watershed for the current conditions, and scenarios 1 and 2. For scenarios 1 and 2, the maximum numbers of monitoring stations were used to determine the variations. These results show that the median of actual SR is close to the lumped SR. It can be assumed that the higher average SRs caused by the outliers of the SRs are from the low salinity producing watersheds.

Proposed Monitoring Stations

Tables 1 and 2 show the proposed number of monitoring stations of the seven selected watersheds using an arbitrarily chosen target SR of 25. The watersheds were selected from the top 1, 10, 20, 30, 40, 50, and 59 among 59 watersheds according to the salt loads. The target SR of 25 is an arbitrary number for demonstration purposes, and the value can change to any other number between zero and maximum SR for a given scenario. The fifth column of Table 3-1 shows the number of monitoring stations required to satisfy the target SR using equation (2). The next column shows the change that can be accommodated under scenario 1 from the differences between the designated number from the equation (3) and the current number of stations. A positive value suggests the number of potential stations that can be added under scenario 1, while a negative value indicates the redundant number of stations. Among the seven selected watersheds, HUC 14060003, 14070006, 14050003, and 14040102 have insufficient number of monitoring
stations for the given target SR, such that these require more monitoring stations considering the available stations under scenario 1. The available stations under scenario 1 in HUC 14020003 is three while the required number is still one, therefore the number does not have to be changed. In HUC 14060008, the current number of stations, available number of stations under scenario 1, and the target number from the SR were estimated at one stations in the watershed. Therefore, it can be assumed that there is an adequate number of monitoring stations in HUC 14060008 under scenario 1 with a target SR of 25. The required number of stations in HUC 14070004 using the target SR of 25 was calculated at zero because of the low salt loads. However, a minimum threshold of at least one station is maintained in each watershed. Similarly, Table 3-2 suggests the hydrometric network using the same condition with Table 3-1 except scenario 2. The number of monitoring stations from the current condition in 2011 and from the target SR remains same, but the available number of monitoring stations was increased under scenario 2. Because of sufficient availability, HUC 14050003 and 14040102 meet the requirements of the target SR while HUC 14060003 and 14070006 still need additional monitoring.

When the water quality load in individual watersheds is compared with the existing monitoring stations, the proposed approach indicates that it will be effective to move the excess monitoring stations from redundant watersheds to watersheds where monitoring stations are scarce. The systematic approach of using SR is based on both salt loads and the existing monitoring stations in watersheds, and therefore, provides a consistent scientific basis to allocate resources for long-term monitoring.
Spatial Distributions of Monitoring Stations

Figure 3-4 shows the spatial distribution of changes of monitoring stations for scenarios 1 and 2. The target SR values were set to 25 and 50 for each scenario. The redundancy or scarcity of the number of monitoring stations in each watershed is presented. Watersheds colored blue require more monitoring stations and the corresponding number required is indicated inside each watershed. Numbers within red watersheds represent the number of redundant stations within each watershed. White watersheds have an adequate number of monitoring stations. Using a target SR of 25 in scenario 1, there are 28 watersheds that require a total of 72 more monitoring stations, while 7 watersheds have 10 redundant monitoring stations. By changing the target SR to 50, the proposed number of monitoring stations increases. Thirty watersheds require more monitoring stations, and the corresponding number of monitoring stations to be added is 95. The number of redundant stations decreases to 6 in 5 watersheds. The scarcity in HUC 14010001, Colorado Headwaters, is the highest where it requires 9 more monitoring stations using the target SR of 25, and 14 more monitoring stations using the target SR of 50. On the contrary, redundancy is the highest in HUC 14050006, White-Yampa, where redundancies are 3 and 2 with target SR values of 25 and 50, respectively.

Scenario 2 considers an inventory of approximately two-and-a-half times more monitoring stations than scenario 1, such that there is more opportunity to meet target SR values. This feature of scenario 2 produces more scarcity for the same SR than scenario 1. Contrary to scenario 1, HUC 14010005, Colorado Headwaters-Plateau, is the watershed which requires the highest number of monitoring stations for both target SR values of 25
and 50. This watershed needs 12 and 23 more stations for the target SR values of 25 and 50, respectively. The watershed with the most number of redundant stations for scenario 2 is same with scenario 1 which is HUC 14050006, White-Yampa, and the redundant numbers are 3 and 2 for the target SR values of 25 and 50, respectively.

Variation of the Number of Monitoring Stations with Target SR

Figure 3-5 shows the relationship between the target SR, the proposed number of monitoring stations, and the actual SR which can be calculated using the proposed number of monitoring stations. The target was first selected arbitrarily from zero to the maximum target SR which comes from the maximum number of monitoring stations of each scenario. Then, the proposed number of monitoring stations was calculated by comparing the number from the target SR and the available stations. Lastly, the actual average SR among 59 watersheds in the UCRB was calculated. The estimated relationship shown as curved line can be regarded as the line of the effective monitoring station distribution. If too many monitoring stations are located in the low salinity producing watersheds and too few stations are located in the high salinity producing watersheds, the corresponding point in Figure 3-5 will move below the line of effective distribution. On the contrary, a hydrometric network which excessively focuses on high salinity producing watersheds makes the relationship to move above the line of effective distribution. In all plots in Figure 3-5, the relationships between SR and the number of monitoring stations from the current conditions are located below the line of effective distribution, resulting in additional monitoring efforts in high salinity producing watersheds.
Impacts of Monitoring on Water Quality Modeling

This work was motivated by the decreasing trend of monitoring stations observed during salinity modeling in the UCRB. Keum and Kaluarachchi (2014) performed SPARROW salinity modeling using available data, but the results from limited information may be questionable. It is difficult to determine the adequacy of monitoring for providing reliable estimates. To analyze this adequacy, we propose to study the impact of monitoring data on water quality modeling. Considering the fact that 7 million tons of salts passing through the outlet of UCRB, 64 monitoring stations in 2011 seems inadequate. Incremental load predictions from SPARROW 2011 (Keum and Kaluarachchi, 2014) were used as the incremental salinity loads from watersheds. Since loads produced from the SPARROW model are not observed loads but predicted loads, noise was added to the predicted loads to introduce model uncertainty. From the existing SPARROW 2011 model, the residuals differences between the observed and predicted loads were close to a normal distribution. Therefore, the noise was calculated using the same statistical distribution of residuals from the SPARROW 2011 model. The computed noise was thereafter added to the predicted salt distribution of SPARROW 2011.

Fifteen SPARROW model runs were conducted for each selected target SR and scenario to determine the statistical variation of model uncertainty. The monitoring stations in a watershed were randomly selected for each model run. Figure 3-6 shows the SPARROW model statistics by changing the target SR for scenarios 1 and 2, and Table 3-3 gives the relationship between the target SR and the corresponding number of monitoring stations. The statistics such as root mean square error (RMSE) and the
coefficient of determination for salinity yield (Yield $R^2$) (equations 1 and 2, respectively, (Schwarz et al., 2006)) describe that the model uncertainty decreases with the increase of target SR and the number of monitoring stations. It should be noted that the Yield $R^2$ is the $R^2$ value of the logarithm of contaminant yield by removing strong correlation between source variables and drainage area.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} \hat{e}_i^2}{N-K}}$$

(1)

where RMSE is the dimensionless root mean square error, $\hat{e}$ is the estimated residual in log space, $N$ is the number of observations, and $K$ is degrees of freedom.

$$\text{Yield } R^2 = 1 - \frac{\sum_{i=1}^{N} e_i^2}{\sum_{i=1}^{N} \{(f_i^*-\bar{f}^*)-(d_i-\bar{d})\}^2}$$

(2)

where $e_i$ is the residual at the monitoring station $i$ in log scale, $N$ is the number of monitoring stations, $f_i^*$ is the observed flux at the monitoring station $i$ in log scale, $\bar{f}^*$ is the mean observed flux over $N$ observations, $d_i$ is the drainage area of the monitoring station $i$ in log scale, and $\bar{d}$ is the mean drainage area over $N$ monitoring stations.

In specific, if the target SR is given as 10, the variation of RMSE between whiskers in Figure 3-6 is greater than 0.1 and 0.15 for scenario 1 and 2, respectively. However, the variation of RMSE is around or less than 0.01 if the target SR is 150. The boxplots using Yield $R^2$ show a similar pattern indicating the variations are large with a limited number of monitoring stations and vice versa. As shown in Figure 3-6, the variations of statistic parameters noticeably change between the SR of 25 and 50. Therefore, the minimum SR target value of 25 is recommended for reliable SPARROW salinity modeling in the UCRB using the 2011 conditions. Consequently, it is shown that
the current condition of 64 active salinity monitoring stations in the UCRB produce a large statistical variation. This observation suggests that the SPARROW 2011 model results can be made more reliable if monitoring stations are added in a manner similar to the proposed approach.

SUMMARY

Due to the financial and management issues, the number of the active monitoring stations in the US has decreased significantly during the past few decades. The decreasing trend is a concern in modeling and management, because model uncertainty increases with limited observations. Therefore, effective monitoring strategies with limited budgets are important from a management viewpoint. In this work, a decision-making framework for establishing an effective water quality monitoring network is developed. As a metric of effectiveness, station ratio (SR) which represents the relationship between the number of monitoring stations and the incremental water quality load within a watershed is proposed. If the total number of monitoring stations for a basin is set according to the available budgetary resources, the corresponding target SR and the number of monitoring stations in the individual basin can be estimated. This proposed SR-based analysis was conducted to identify the adequacy of the existing hydrometric network and to propose the potential needs in salinity monitoring in the UCRB at 8-digit HUC scale. The results from the SR estimations demonstrate that the current salinity monitoring network can be improved by establishing denser network on high salinity producing watersheds, because the monitoring within those watersheds is typically scarce. In specific, the scarcity of salinity monitoring is highest in HUC 14010001,
Colorado Headwaters, while the redundancy is highest in HUC 14050006, White-Yampa. Uncertainty analysis about SPARROW salinity modeling also concluded that the number of monitoring stations were not enough due to the large statistical variability of uncertainty. The variation of RMSE and $R^2$ is considerable between the target SR values of 25 and 50. Therefore, it can be assumed that a target SR of no less than 25 is recommended for salinity monitoring in the UCRB using 2011 data.

The proposed decision-making procedure is scalable to any water quality monitoring network, and provides the information required to allocate available resources to develop an effective monitoring network. However, the procedure proposed in this research has limitations too. This work has focused exclusively on optimizing the monitoring network for salinity in the UCRB. However, water quality interests in other watersheds can be a combination of one to many water quality parameters, and can be dependent on site-specific conditions. Future work in this aspect needs to be developed further to understand how multiple water quality parameters can be accommodated in the overall establishment of a monitoring network. Also, this simple and pragmatic approach of developing a monitoring strategy will identify the monitoring needs at watershed scale but the actual location within the watershed is not specified. Additional analysis may be needed in such situation to identify the specific locations of additional monitoring stations. One advantage of this simple decision-making approach is that the work can be easily extended to identify the cost and equity considerations in allocating monitoring responsibilities among different stakeholders in a watershed.
LITERATURE CITED


Table 3-1. Sample calculations for the proposed number of monitoring stations using scenario 1 and target SR of 25. In all cases, a minimum threshold of one station is maintained in each watershed. The positive numbers represent deficit and negative represent redundancy.

<table>
<thead>
<tr>
<th>Watersheds (HUC8)</th>
<th>Salt Loads in 2011 (tons/year)</th>
<th>Number of Monitoring Stations</th>
<th>Available under Scenario 1</th>
<th># Stations required for Target SR</th>
<th>Deficit / Redundancy from Target</th>
<th>Suggested Number under Scenario 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>14060003</td>
<td>687,564</td>
<td></td>
<td>5</td>
<td>7</td>
<td>17</td>
<td>12</td>
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<tr>
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<td>1</td>
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<td>6</td>
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</tr>
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</tr>
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<td>14020003</td>
<td>27,266</td>
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<td>0</td>
</tr>
<tr>
<td>14070004</td>
<td>8,685</td>
<td></td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>-1</td>
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</table>
Table 3-2. Sample calculations for the proposed number of monitoring stations using scenario 2 and target SR of 25. In all cases, a minimum threshold of one station is maintained in each watershed. The positive numbers represent deficit and negative represent redundancy.

<table>
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<tr>
<th>Watersheds (HUC8)</th>
<th>Salt Loads in 2011 (tons/year)</th>
<th>Number of Monitoring Stations</th>
<th># Stations required for Target SR</th>
<th>Deficit / Redundancy from Target</th>
<th>Suggested Number under Scenario 2</th>
</tr>
</thead>
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<td></td>
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<td>Available under Scenario 2</td>
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<td>27,266</td>
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</tr>
<tr>
<td>14070004</td>
<td>8,685</td>
<td>1</td>
<td>2</td>
<td>0</td>
<td>-1</td>
</tr>
</tbody>
</table>

Note) The positive numbers in the column of Deficit/Redundancy represent deficit, and the negative means redundancy.
Table 3-3. Target SR and the corresponding total number of monitoring stations in the UCRB for scenarios 1 and 2.

<table>
<thead>
<tr>
<th>Target SR</th>
<th>Number of Monitoring Stations</th>
</tr>
</thead>
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<td>Scenario 1</td>
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<tr>
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<td>100</td>
<td>164</td>
</tr>
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<td>150</td>
<td>167</td>
</tr>
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</table>
Figure 3-1. Variation of the number of salinity monitoring stations in the UCRB from 1991 to 2011.
Figure 3-2. Spatial distribution of monitoring stations and the predicted salinity loads in the UCRB in 2011.
Figure 3-3. Distributions of the actual SR compared to the lumped SR for the 2011 condition, and scenarios 1 and 2.
Figure 3-4. Spatial distributions of proposed monitoring network for scenarios 1 and 2 with target SR values of 25 and 50; (a) scenario 1 with target SR of 25, (b) scenario 1
with target SR of 50, (c) scenario 2 with target SR of 25, and (d) scenario 2 with target SR of 50. The numbers inside watersheds indicate the numbers to be added or reduced.
(c) Scenario 2
Target SR = 25
(d) Scenario 2
Target SR = 50

North America Albers Equal Area Conic Projection, NAD 1983

UCRB: Upper Colorado River Basin
LCRB: Lower Colorado River Basin

Active Stations in 2011

Redundant
Adequate
Scarce
Figure 3-5. Relationships between the number of monitoring station and SR for scenarios 1 and 2.
Figure 3-6. SPARROW simulation statistics from 15 runs for randomly selected monitoring stations with changing the target SR. (a) and (b) for scenario 1, and (c) and (d) for scenario 2.
CHAPTER 4

SALINITY MANAGEMENT IN THE UPPER COLORADO RIVER BASIN WITH COST-EQUITY CONSIDERATIONS

ABSTRACT

Establishing an effective water quality management strategy is important not only for pollution control but also for long-term cost saving and to address stakeholder concerns. Salinity buildup in the Upper Colorado River Basin (UCRB) has been a serious concern for the past few decades, and therefore, management of salinity control through an effective distribution of salinity control responsibilities among watersheds is important. A practical framework to allocate responsibility for salinity reduction is developed in this work considering cost-effectiveness, equity, and their trade-offs. The proposed framework was applied to the UCRB using salinity data from 2011 and the calibrated water quality model SPARROW. A base scenario using the allocation of responsibility simply by percentage of irrigated lands is proposed together with a typical cost minimization scenario for comparison purposes. Equity criteria are defined by salinity control costs, available quantity for salinity control, irrigated land area, and net agricultural income. Among the proposed six scenarios, equity for the salinity control cost and cost minimization give similar results of which the total control cost is the lowest and the equity scores are good. Scenarios with equity for the maximum possible salinity control quantity and for irrigated land area show higher total control costs compared to other scenarios. Temporal variability of allocation shows that responsibility

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3 Coauthored by Jongho Keum and Jagath J. Kaluarachchi
decreases with time due to the effectiveness of the existing salinity control programs. The trade-off curve represents the most cost effective solution for a given equity score. As the curves vary logarithmically, the marginal cost increases with improved equity score. The proposed framework allows decision-makers to allocate water quality control responsibilities for a given control target using cost and equity as principal considerations.

INTRODUCTION

The Colorado River system serves water to nearly 36 million people mostly for municipal uses, and irrigation water for 5.5 million acres of agricultural lands (US Department of the Interior, 2013). The municipal water use includes deliveries to the residential, commercial, and industrial sectors in the Colorado River Basin and trans-basin diversions (Cohen, 2011; Colorado River Basin Salinity Control Forum, 2011). Unfortunately, the Colorado River is naturally saline due to its geologic conditions (Miller et al., 1986; Timothy et al., 1988; Hayes, 1995; Patrick, 2000; Tuttle and Grauch, 2009). Tuttle and Grauch (2009) found that most of the salts are derived from geochemical interactions of water with soil, alluvium, and rock formations in the Upper Colorado River Basin (UCRB). In addition to the natural weathering, anthropogenic activities such as irrigation become the additional contributors for releasing saline ions to groundwater and surface water (Watts and Teel, 2003; Tuttle and Grauch, 2009). With excess salinity in water, the socioeconomic damage in the UCRB is unavoidable. US Department of the Interior (2013) estimated the economic damages in the Colorado River Basin as $295 million per year using salinity concentration data of 2010. Similarly, Houk
et al. (2006) concluded that salinity has negative effects on crop production and the corresponding agricultural income.

A number of studies analyzed the salinity trends, and concluded that increasing trends have not been found in the UCRB due to the effectiveness of the existing salinity control programs (Butler, 1996; Bauch and Spahr, 1998; Anning et al., 2007; Colorado River Basin Salinity Control Forum, 2011). On the other hand, statistical or stochastic salinity models were developed to simulate salinity in the UCRB (Mueller and Osen, 1988; Lee et al., 1993; Prairie et al., 2005; Prairie and Rajagopalan, 2007). Anning et al. (2007) used SPARROW water quality model developed by Smith et al. (1997) to analyze salinity, as dissolved-solids, in the southwestern United States. Kenney et al. (2009) focused on the UCRB, and calibrated salinity sources and transport for the year 1991. The temporal transferability of the calibrated SPARROW salinity model for 1991 was adequate using data for the years 1974 to 1998 (Kenney and Buto, 2012). However, the model transferability was not evaluated to the recent years due to lack of data, and the model will be vulnerable to abnormal climatic and hydrologic conditions. For these reasons, Keum and Kaluarachchi (see Chapter 2) conducted a study using SPARROW model with data from the recent decade and suggested an individual calibration process for each year to improve accuracy of the simulation results.

In the Colorado River Basin, the numeric criteria and a Plan of Implementation were initially proposed by the Colorado River Basin Salinity Control Forum, adopted by the seven states which include parts of the Colorado River Basin, and approved by US Environmental Protection Agency (EPA) in 1975 (Colorado River Basin Salinity Control
The numeric criteria were given as flow weighted average annual salinity concentrations in 1972 at three locations on the main stem of the lower Colorado River; 723 mg/L below Hoover Dam, 747 mg/L below Parker Dam, and 879 mg/L at Imperial Dam, respectively, and these numerical criteria have been maintained to date (Colorado River Basin Salinity Control Forum, 1975, 2011). Because the salinity control efforts focus on the UCRB more than the lower Colorado River Basin, Keum and Kaluarachchi (see Chapter 2) suggested a numeric criterion at the outlet of the UCRB, Lees Ferry, Arizona, as 566 mg/L which is derived from the flow weighted average annual salinity concentration data of 1972. Even though the annual salinity concentration has been maintained below the representative criterion at the outlet of the UCRB (see Chapter 2), the probability of exceeding the numeric criteria in the Colorado River will increase without further salinity control measures (Colorado River Basin Salinity Control Forum, 2011). The past plan of implementation of salinity control by the Bureau of Reclamation (BOR), US Department of Agriculture (USDA), Bureau of Land Management (BLM), and Basin States Program has worked effectively, resulting in the annual average salinity concentration under the numeric criteria (Colorado River Basin Salinity Control Forum, 2011; see Chapter 2). The Colorado River Basin Salinity Control Forum (2011) suggested the potential future areas of management by evaluating the improvements of agricultural practices. While there have been many previous studies conducted to manage salinity in the UCRB, studies related to establishing effective salinity control and corresponding allocation strategies to achieve the salinity criteria is still limited.
Traditionally, the lowest cost solution is considered the most effective management approach, in this case, the provided outcome is reduced salinity. However, in reality, factors affecting salinity control such as the salinity contribution to the main stem, options to reduce salinity or agricultural incomes are different in each watershed. Therefore, cost minimizing strategy can neglect the fairness in the allocation of salinity control responsibilities among the stakeholders. Khadam and Kaluarachchi (2006) introduced equity as a measure to compare the different pollution mitigation solutions in the allocation of phosphorus reduction responsibilities among participating watersheds. Trade-off curves between cost efficiency and equity were estimated by calculating total phosphorus reduction costs which satisfy certain equity scores. These trade-off curves can help decision-makers select the optimal solution considering the different interests of the stakeholder groups. Accordingly, the purpose of this work is to develop a similar approach of introducing equity as a measure in a decision-making framework for salinity control in the UCRB. In this case too, the different attributes representing the different stakeholder concerns will be used and the cost of salinity control options will be compared against equity and cost efficiency. The goal here is to provide the decision-maker with a framework that can generate and demonstrate trade-offs between different salinity control options considering simultaneous representation of both cost and equity. In order to achieve this purpose, six different scenarios are proposed for the UCRB including cost minimization and equity maximization. In addition, trade-offs between cost efficiencies and equity scores are also evaluated.
BACKGROUND

Salinity Modeling in the UCRB

The study area is the UCRB located in the southwestern United States and shown in Figure 4-1. The drainage area of the UCRB is 280,000 square kilometers and is comprised of parts of five states; Wyoming, Colorado, Utah, New Mexico, and Arizona. Approximately 7 million tons of salts are transported annually through the outlet of the UCRB, Lees Ferry, Arizona (Anning et al., 2007; see Chapter 2).

SPARROW (SPAtially Referenced Regressions On Watershed attributes) surface water quality model is a hybrid, semi-distributed, stochastic model that is capable of predicting salinity production from each watershed or drainage using mass balance. The mathematical model of SPARROW consists of nonlinear weighted least squares regression of flux transport function using mass balance and spatially distributed physical parameters (Schwarz et al., 2006). The transport function is defined by conservation of mass; load passing through the outlet of a reach is comprised of load received from the upstream reaches and load released within the catchment of the reach. Therefore, SPARROW requires a hydrologic network which represents the connections of stream reaches.

Anning et al. (2007) used SPARROW to simulate salinity in the southwestern United States including the UCRB. Kenney et al. (2009) and Kenney and Buto (2012) studied salinity in the UCRB for the hydrologic normal year and its transferability to other years. While Kenney and Buto (2012) concluded that the transferability of the calibration results from a representative year were applicable, Keum and Kaluarachchi
(see Chapter 2) suggested individual calibrations using the best available information for the given years, and conducted SPARROW simulation from 1999 to 2011. The modified complementary method was applied to overcome the lack of evapotranspiration data (see Chapter 2). In this work, SPARROW calibrated by Keum and Kaluarachchi (see Chapter 2) was used to model salinity in the UCRB.

**Salinity Management**

In public lands, major causes of Colorado River salinity are soil erosion and saline springs, while irrigated water has become the major sources in private lands (US Department of the Interior, 2003). Since the Colorado River Salinity Control Act of 1974 (Public Law 93-320) was enacted, federal agencies such as US Department of Agriculture (USDA), Bureau of Reclamation (Reclamation), and Bureau of Land Management (BLM) have installed salinity control programs to meet the salinity control needs. BLM has controlled salinity in the UCRB by preventing soil erosion on public lands; for example, vegetation management, land treatment, and structural construction (US Department of the Interior, 2003). Salinity control projects by Reclamation were installed by the proponents and selected by considering not only cost effectiveness but also performance risks (US Department of the Interior, 2003). On the other hand, USDA mostly focuses on salinity controls from the irrigated lands by preventing water loss such as installation of ditch, lining, pipe, or enhanced irrigation systems (US Department of the Interior, 2003). Salinity controls in the private lands are typically more effective than those in the public lands. Also, the US Department of the Interior (2011) estimated about 37% of salinity in the Colorado River Basin is due to agricultural activities while only
2.7% of the basin area is occupied by irrigated lands. Therefore, salinity control in irrigated lands is considered as the first step of developing the decision-making framework.

The cost function of salinity control is defined by the relationship between the reduced mass of salts from a salinity control program and its corresponding cost. Since USDA has implemented salinity control projects mostly in irrigated lands, the salinity control amount and the annual salinity control costs by the actual USDA salinity control units were gathered to define the cost function. Because the most recent SPARROW model was developed for 2011 (see Chapter 2), the relationship between salinity control quantity and the corresponding cost in 2010 were obtained from the US Department of the Interior (2011). Figure 4-2 shows the relationship and the estimated cost function using regression analysis. The cost function fits best (i.e. high R-squared value as 0.97) to a quadratic function which comes with a linear increasing marginal cost. In the regression analysis, the cost function was forced to pass the origin because no action requires no cost. The estimated cost function is given by

\[ C = 2.5830 \times 10^{-10}TDSr^2 + 1.9239 \times 10^{-2}TDSr \]  \(\text{(1)}\)

where \(C\) is the annualized salinity control cost ($/year) and \(TDSr\) is the amount of salinity control (kg/yr). The annualized control costs were estimated using the total project cost and amortization over 25 years (US Department of the Interior, 2011).

It is estimated that 1.85 million tons of salinity per year should be removed through 2030 to avoid exceeding the salinity criteria and the associated socioeconomic damage (US Department of the Interior, 2011, 2013). Federal agencies, such as
Reclamation, USDA, and BLM, have constructed salinity control programs, and the controlled salinity mass was estimated at 1,192,100 tons by 2010 (US Department of the Interior, 2011). Therefore, the total remaining salinity control target used in this work is set to 657,900 tons in 2011. Since this work focuses on the allocation of salinity control responsibilities in irrigated lands only, a portion of irrigation induced salinity is also considered in this work.

METHODOLOGY

Equity Criteria

Equity in water and environmental management represents an equitable distribution of natural resources such as water rights, or pollution control or mitigation responsibilities related to water born contaminants or carbon dioxide in the atmosphere. In this work, equity is represented by an equity score for a given salinity control measure among the different watersheds and the equity score is estimated using the following attributes: (1) salinity control cost, (2) possible maximum salinity control mass, (3) irrigated land area, and (4) net agricultural income.

Control costs are simply estimated by the cost function given by equation (1) and the estimated salinity control mass required in each watershed. Equity for the control costs means proportional or equitable economic sharing of burden among stakeholders which in this case are salinity producing watersheds. Next, equity for possible maximum salinity control mass implies a watershed which has the higher potential salinity control mass takes more control responsibility compared to another watershed than has lower potential salinity control mass. As assumed in this research, salinity control programs are
targeting irrigation lands only for the portion of salt produced from irrigation. In other words, possible maximum salinity control mass corresponds to the complete retirement of irrigated lands. In this case, salinity is produced by existing geologic sources of the watersheds only. For this purpose, SPARROW was simulated under existing conditions and with irrigated land retired. The difference in results between the simulations can provide the maximum salinity control mass due from irrigated lands of the UCRB (see Chapter 2).

Thirdly, equity due to irrigated land area denotes that watersheds with more irrigated land area holds more responsibility for salinity control than a watershed with less irrigated land. This criterion is considered because the salinity control programs are assumed to be installed in irrigated lands. The last equity attribute to consider is the agricultural income derived from irrigated agriculture because agriculture production and the corresponding economic benefits are different between irrigated lands. The production costs and income depend on various factors, such as the crops grown, the amount of water used, and the applied chemical treatments. Therefore, net agricultural income data are obtained from census data of 2007 conducted at the county-level for net cash farm income by USDA, Census of Agriculture (US Department of Agriculture, 2007). The income value itself is not suitable to apply to the equity measures directly because some of these have negative or zero values. Therefore, income index is proposed to avoid zero or negative denominator in calculating equity. The proposed income index, $I_{CI}$, ranges from one to two, and is given by

$$I_{CI} = \frac{IC_{i} - I_{C_{min}}}{IC_{max} - I_{C_{min}}} + 1 \quad (2)$$
where $IC_i$ is income index of watershed $i$ (dimensionless), $IC_i$ is net agricultural income of watershed $i$ ($$/year), $IC_{min}$ is the smallest net agricultural income among all watersheds ($$/year), and $IC_{max}$ is the largest net agricultural income among all watersheds ($$/year).

**Equity Measures**

The equity measures are formulated by a mathematical combination of two criteria; effect and attribute. Effect is a level of distribution to share fairly, i.e. salinity control responsibility of a watershed in this work. On the other hand, attribute means a characteristic which becomes the decision-making standard, such as the equity criterion or attribute described in the previous section. In this work, the attributes become the equity criteria which include control cost, possible maximum salinity control mass, irrigated land area, or net agricultural income. Depending on the structure of an equity measure, equity score may vary significantly. In order to compare the estimated equity scores among one another, normalized equity measures, e.g. dimensionless equity, are required. Marsh and Shilling (1994) suggested peer, mean, and attribute types for the normalized reference distribution. The term ‘distribution’ implies a set or distribution of effects among stakeholders (i.e., salinity control responsibility in each watershed) for a given scenario. These reference distributions are divided by which group would be compared with. The peer reference distribution estimates equity score by pairwise comparison with the effect on a group, while the mean reference distribution compares the individual effect with the mean effect. The attribute reference distribution compares each attribute and its effect. There is no clear answer which reference distribution should
be used in an allocation problem such as salinity control in the UCRB. Therefore, all three reference distributions were used to estimate the equity scores.

First, peer reference distribution is also known as Gini coefficient and given by

$$\text{EP} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \left| \frac{TDSr_i}{ATT_i} - \frac{TDSr_j}{ATT_j} \right|}{2n^2 \frac{TDSr}{ATT}}$$  \hspace{1cm} (3)

where EP is equity score using the peer reference distribution (dimensionless), n is number of watersheds, TDSr$_i$ is salinity control responsibility of watershed i (kg/year), and ATT$_i$ is attribute of watershed i which can be control cost ($/year), maximum possible salinity control quantity (kg/year), irrigated land area (km$^2$), or net agricultural income of watershed i ($/year) as discussed previously. This framework allows the comparison of the ratio between salinity control responsibility and attribute of watershed with each other. The peer reference distribution or Gini coefficient is commonly used to assess equity in various economic and location problems (Erkut, 1993; Ogryczak, 2000).

Equity measure using mean reference distribution is formulated by comparing the ratio between salinity control responsibility or mass and attribute of each watershed to mean of the ratio, and given by

$$\text{EM} = \frac{\sum_{i=1}^{n} \left| \frac{TDSr_i}{ATT_i} - \frac{TDSr}{ATT} \right|}{2n \frac{TDSr}{ATT}}$$  \hspace{1cm} (4)

where EM is dimensionless equity score using mean reference distribution. As shown in equations (3) and (4), EP and EM use the ratio between salinity control responsibility or mass and equity criteria, i.e. attribute.

In the attribute reference distribution, the ratio of salinity control quantity to the average is compared to the same ratio for the attribute. The attribute reference
distribution is given by

\[
EA = \frac{\sum_{i=1}^{n} \left| \frac{TD_{Si}}{TDSr} \cdot \frac{ATT_{Ti}}{ATT} \right|}{2n}
\]  

where \(EA\) is dimensionless equity score using attribute reference distribution. These three equity measures have a similar framework. In the perfectly equitable share of responsibility, the equity score, \(EP\), \(EM\) or \(EA\), will be zero. As the distribution of responsibility becomes gradually less equitable, the equity score increases beyond zero. Hence, minimizing the equity score is synonymous with maximizing the equitable share.

**Scenario Development**

The most simple management scenario is to allocate costs based on the percentage of irrigated lands in each watershed. However, economic aspects are important in management, hence, the obvious goal of cost effective management is to minimize the total cost of salinity control across all watersheds of the entire UCRB. When developing management scenarios, equity among the salinity control responsibility is also an important consideration for stakeholders besides the total control cost for the entire basin. This study considered these competing goals and developed the following management scenarios for irrigated lands:

- **Scenario 1**: This is also the base scenario consisting of cost allocation using the percentage of irrigated land in each watershed (no optimization and equity considerations)
- **Scenario 2**: Minimize the total salinity control cost for the entire basin (optimization with no equity consideration)
- **Scenario 3**: Minimize equity reference distribution with control cost as the attribute (optimization and equity consideration)
- Scenario 4: Minimize equity reference distribution with possible maximum salinity control quantity as the attribute (optimization and equity consideration)
- Scenario 5: Minimize equity reference distribution with percent irrigated land area as the attribute (optimization and equity consideration)
- Scenario 6: Minimize equity reference distribution with net agricultural income as the attribute (optimization and equity consideration)

As given here, only scenarios 3 through 6 provide true equity considerations.

Optimization is performed for scenarios 2 through 6. In the analysis of simulation results, results of scenario 1 and 2 will be used to back calculate the corresponding equity scores. In each case, all three equity measures, EM, EP and EA, will be computed and compared.

Scenario 1 uses irrigated land area as the standard of distribution, and does not require optimization or equity consideration. Salinity control responsibilities are estimated by

\[
\text{Scenario 1: } \text{TDS}_{r_i} = \text{TDS}_{r_T} \times \frac{\text{Irr}_I}{\text{Irr}_T}
\]

where \( \text{TDS}_{r_i} \) is salinity control quantity of watershed \( i \) (tons/year), \( \text{TDS}_{r_T} \) is salinity control target (tons/year), \( \text{Irr}_I \) is irrigated land area of watershed \( i \) (km\(^2\)), and \( \text{Irr}_T \) is total irrigated land area in the UCRB (km\(^2\)).

Because the objective of scenario 2 is minimizing the total salinity control cost, the objective function becomes cost function with total salinity target and possible maximum salinity control of each watershed as constraints.

\[
\text{Scenario 2: } \min C = \sum_{i=1}^{n} (a \times \text{TDS}_{r_i}^2 + b \times \text{TDS}_{r_i})
\]

subject to

\[
\sum_{i=1}^{n} \text{TDS}_{r_i} \geq \text{TDS}_{r_T}
\]
\[ TDS_{r_i} \leq TDS_{r_{\text{max},i}} \]

where \( a \) and \( b \) are coefficients of the cost function given by equation (1), and \( TDS_{r_{\text{max},i}} \) is possible maximum salinity control quantity of watershed \( i \) (tons/year).

Scenarios 3 to 6 minimize equity measures (i.e. EP, EM, or EA), with the same constraints as scenario 2. Differences between scenarios are attributes which is defined as ATT in equations (3) to (5).

\[
\text{Scenario 3 to 6 : } \min E \tag{8}
\]

subject to

\[
\sum_{i=1}^{n} TDS_{r_i} \geq TDS_{r_T}
\]

\[ TDS_{r_i} \leq TDS_{r_{\text{max},i}} \]

where \( E \) is equity measure (i.e. EP, EM, or EA) with the corresponding attributes applicable to each scenario. For example, control cost in scenario 3, possible maximum salinity control quantity in scenario 4, irrigated land area in scenario 5, and net agricultural income in scenario 6, respectively.

**Cost Efficiency**

Cost minimization in scenario 2 produces salinity control allocation with the lowest salinity control cost, therefore, scenario 2 provides the best cost efficiency or 100% with minimal cost. As equity is considered, cost efficiency will decrease from 100% due to trade-offs between cost and equity. Therefore, cost efficiency is defined by the level of cost increase for a scenario compared to the lowest cost option or in this case scenario 2, and given by

\[
\text{EFF} = \frac{c_{\text{min}}}{c_{\text{scenario}}} \times 100(\%)
\]
where EFF is cost efficiency (%), $C_{\text{min}}$ is the total salinity control cost of scenario 2, that is, least cost solution, and $C_{\text{scenario}}$ is total salinity control cost of a given scenario or given a level of equity score.

RESULTS AND DISCUSSIONS

Equity and Cost

The results discussed here use data from 2011 and the corresponding salinity simulation results of SPARROW. Table 4-1 shows the salinity control costs and their corresponding optimized equity scores for the different allocation scenarios, considering irrigated lands as the only management option for a total salinity control target of 657,900 tons per year. It should be noted that only four management scenarios are directly related to equity (scenario 3 through 6) while scenarios 1 and 2 are straightforward simple ratio and cost minimizing approaches respectively and do not consider equity. The optimized equity scores for other equity criteria are calculated later using equity reference distributions and the optimized allocation of salinity control responsibilities.

Table 4-1 shows the optimized and back calculated equity scores from 100% salinity control target using the peer reference distribution. If optimization for a scenario, i.e., an equity criterion, is completed, then the optimized value represents the equity score for the scenario. For example, optimized equity score for scenario 3 can be found in the column of equity for the control cost which is 0.0288. Those optimized values are marked with ‘*’. The other equity scores were back calculated with the optimization results and equity equations for each equity criterion. Table 4-2 shows the range of estimated equity
scores for each scenario by presenting the lowest and highest equity scores. The lowest and highest values were chosen from optimized and back calculated equity scores (see Table 4-1). Scenarios 2 and 3 have similar optimization results as shown in Table 4-2, even though the objectives of the two scenarios are different. Because both scenarios are related to the same attribute, salinity control cost, the estimated equity scores and the salinity control costs are similar to each other. In addition, scenarios 2 to 5 give good equity scores among all scenarios, and the control cost of scenarios 2 or 3 are the lowest. On the other hand, scenario 1 where salinity control responsibilities are allocated based on the percentage of irrigated lands gives the second highest control costs, and has worst equity score as well. These results show that scenario 1 which allocates control responsibilities based on simple physical properties, such as irrigated land area distribution, is less cost effective and also less equitable. Among the equity criteria, good equity for salinity control cost and irrigated land can be easily achieved, because the lowest (best) equity scores are estimated by those equity attributes in scenarios 3 and 5. For example, it is obvious that the optimized equity scores for scenarios 3 and 5, minimizing equity with salinity control cost, are same with the lowest equity scores for the scenarios. In addition, the lowest equity scores of scenarios 4 and 6 are from back calculated equity scores for the salinity control cost as well. On the other hand, the highest (worst) equity scores are typically found with equity for possible maximum salinity control quantity or net agricultural income. The optimized equity scores in Table 4-2 also show that equity for possible maximum salinity control quantity and net agricultural income are generally greater than those for salinity control cost and irrigated
lands. Although equity for net agricultural income itself is minimized, the optimized minimum equity scores are greater than 0.18 while most other optimized equity scores are less than 0.03. It should be noted that the optimized equity score for scenario 4 using mean equity reference distributions gives zero which means perfect equity. However, the corresponding annualized costs increased significantly, resulting in a large economic compensation for this excellent equity. The estimated annualized costs for scenarios 2 and 3 are the lowest, and that of scenario 6 is similar but little higher. Although equity with net agricultural income is selected as the most common in decision-making, the total salinity control costs will not increase significantly. On the other hand, targeting scenario 4 or 5, i.e. equity for possible maximum salinity control quantity or irrigated land area, tends to increase the total control cost. Scenario 4 using mean equity reference distribution charges about 27% more control cost compared to cost minimization.

Statistical box plots for all scenarios using the peer reference distribution are given in Figure 4-3. The results show the distributions of salinity control responsibilities from 59 watersheds. Median values of scenarios 1 and 5 are relatively low, while those for scenarios 2, 3, and 6 are high. In other words, a small number of watersheds, outliers in the plot should bear significant amounts of salinity control in scenarios 1 and 5. On the other hand, the total control target tends to be distributed equally in scenarios 2, 3, and 6, resulting in higher average control responsibilities compared to other scenarios.

Equity scores and the corresponding annualized salinity control costs were estimated for additional water quality targets as well. These targets were arbitrarily selected for demonstration purposes and the values are 75% and 50% of the total salinity
control target. In addition, 37% of the total control target was also considered to represent the amount of salinity from irrigation. The results are shown in Table 4-3. The total control costs, decrease rapidly with the decrease of water quality target, because the cost function is quadratic. However, the equity scores and the relative cost distributions do not change significantly with each salinity control target, and therefore, the earlier conclusions are still valid. Scenarios 2 and 3 provide good equity and the lowest control costs, while scenarios 4 and 5 produce higher annualized costs compared to other scenarios.

Spatial Distribution of Salinity Control Responsibility

Figure 4-4 shows the spatial distribution of salinity control responsibilities between different watersheds for four selected scenarios; 1, 2, 5, and 6, using the peer equity reference distribution. Scenario 1 used the percentage of irrigated lands to estimate costs while scenario 5 used irrigated land area as the attribute in minimizing equity. Therefore their salinity control responsibilities show a similar pattern with the distribution of irrigated lands in the UCRB. In such scenarios, a higher salinity control responsibility is given to a watershed with larger irrigated land area. On the other hand, the map of scenario 2, cost minimization, presents similarly distributed allocation. Because the cost function is quadratic, the cost of salinity controls increases significantly when a small number of watersheds are given the task of reducing a large quantity of salinity. Therefore, scenario 2 tends to distribute the total salinity control target across the entire basin equally based on the maximum possible salinity quantity that can be removed from each watershed. The allocation produced by scenario 6 is more equally distributed.
than scenarios 1 or 5, because both the irrigated lands and the productivity of agricultural activities are related to the predicted allocation of salinity control responsibilities. The results from scenario 3 were similar to scenario 2, and those from scenario 4 showed relatively intermediate responsibilities between scenarios 2 and 5.

Temporal Variation

The previous simulations demonstrated the importance of equity and trade-offs between cost and equity in salinity management for data and results from 2011. In this section, the years prior to 2011 were selected to assess the effects of time variability. In general, salinity production varies temporally due to the temporal variability in hydrologic conditions. The US Department of the Interior (2003, 2005, 2011) proposed salinity control targets in the Plan of Implementation by estimating the cumulative target of salinity control and the effectiveness of salinity control measures already in place. The salinity control target in 2002 and 2004 were 1,000,000 and 728,000 tons per year, respectively (US Department of the Interior, 2003, 2005). For this reason, 2002, 2004 and 2011 were selected to study the effect of temporal variation on salinity control.

Figure 4-5 shows the spatial distribution of salinity control in 2002, 2004, and 2011 using the peer equity reference distribution and 37% of the total target representing salinity from irrigated lands. There are larger areas which had high salinity control responsibilities in 2002, but those areas have decreased in 2004 and 2011. Figure 4-6 shows the histogram to verify this trend. The plot shows the number of watersheds that responded with salinity control responsibilities. The salinity control responsibilities of most watersheds were about 10,000 tons per year in 2002, and this number reduced to
around 6,000 tons per year in 2004, and then to 5,000 tons per year in 2011. This observation also confirms the effectiveness of the existing salinity control programs.

**Cost Efficiency**

To demonstrate the concept of cost efficiency in the trade-offs between equity and cost efficiency, scenario 5 using the irrigated land area was selected, because of its large variability of equity scores. The results are shown in Figure 4-7 for all three equity reference distributions; peer, mean, and attribute. Data points of the trade-off curves are estimated using cost minimization with equity constraints to meet a given equity score. The optimization problem is solved repeatedly for different equity constraints between the lowest and highest scores for the specific equity criterion. For example, the equity score for irrigated land or scenario 5 varies from 0.0175 to 0.5896 for peer equity reference distribution (see Table 1); hence, the calculations are for equity scores within this range only. The constraint added to the scenario is given by

\[ E \leq E_{\text{goal}} \]  

where \( E \) is equity score (EP, EM, or EA according to the equity reference distribution), and \( E_{\text{goal}} \) is a given level of equity score for each calculation or data point.

Figure 4-7 shows the cost-equity trade-off curves which indicate cost-efficiency decreases when equity score increases. This observation is similar to work of others found in phosphorous management to the lower Nooksack River Basin in Washington State (Khadam and Kaluarachchi, 2006). In addition, the trade-off curves divide the plot into two distinct regions. The lower part of the curve denotes the feasible solution region, and the solution becomes more effective if it is closer to the curve. The results also show
that the cost efficiency values are different between equity reference distributions; however, the shapes of these trade-off curves are similar. Hence, the selection of the equity reference distribution has little effect on the variation of cost efficiency. The results, therefore, indicate that as the expected equity increases beyond the lowest value (or minimum cost), the corresponding cost increases thereby decreasing cost efficiency.

CONCLUSIONS

To date, efforts on understanding salinity production, modeling, and control in the UCRB have been conducted continuously. However, studies related to decision-making strategies, such as the location where salinity control is required most, cost of salinity control measures to understand how resources should be allocated, and the corresponding equity among the stakeholders for a given management scenario, are limited. Current salinity control programs on irrigated lands, such as the USDA salinity control units, mostly depend on the improvements of irrigation systems and water supply systems to prevent excessive water loss. For this reason, a decision-making framework for allocation of salinity control responsibilities in the UCRB is developed in this work. The goal of this work is to propose an appropriate decision-making framework and demonstrate its applicability but not to propose a given decision. The eventual goal of this work is to provide the knowledge and insight to the decision-makers including land and water managers so that they are able to implement a similar framework in consultation with stakeholders. One distinct advantage of this type of framework is avoiding conflicts between stakeholders as the decision framework is built on a consistent set of objectives and provides a scientific basis rather than using ad-hoc decisions that may change
frequently.

The proposed framework considers cost of salinity control, equitable distribution among stakeholders (or watersheds), and cost efficiency between different scenarios representing common stakeholder concerns such as income, irrigated land area, etc. Three commonly used equity reference distributions, peer, mean, and attribute, of which peer distribution, or Gini coefficient, in many other decision-making situations, were investigated. To demonstrate the applicability of the proposed framework, six scenarios were developed from the simplest lowest cost option to scenarios maximizing equity under different equity attributes such as total control cost, possible maximum salinity control quantity, irrigated land area, and net agricultural income.

The calculated equity scores and control costs show that allocation according to the percentage of irrigated lands (scenario 1) produces high salinity control cost and poor equity, therefore, efforts on minimizing costs and maximizing equity are important. Scenarios 2 and 3 which are control cost minimizing and equity maximizing for control costs show similar results. However, scenarios 4, 5, and 6 tend to allocate more control responsibilities to some watersheds where the equity criterion, for example, possible maximum salinity control quantity for the scenario 4, is higher. In addition, the comparison between the different equity reference distributions or water quality targets show that the type of distribution or control target does not affect the general outcome. Distributions shown in box plots and spatial maps also confirm the presence of unequal distributions of responsibility for scenarios 4, 5, and 6, while showing similar distributions for scenarios 2 and 3. Temporal variation of allocation of salinity control
responsibilities showed that the salinity control amounts and the areas of high control responsibility have decreased most likely due to the effectiveness of the ongoing salinity control programs. Possible limitation of this equity analysis is uncertainty, especially when the equity scores are close to each other. By considering uncertainty, the distribution of equity scores can be obtained and therefore the corresponding statistics. Once these statistics are known, the equity scores and their relevance in management decision-making will be more apparent than the deterministic analysis conducted here. Therefore, an uncertainty analysis is required in future work to compare contrast the different scenarios.

Trade-offs between cost efficiency and equity score are also calculated for the irrigated area (scenario 5). Since the cost minimization (scenario 2) generally gives the lowest control cost, the cost-efficiency from the scenario become zero. If a specific equity score should be met due to the demands of the stakeholders different to the equity score of the cost minimizing scenario, the cost efficiency will decline. Moreover, the shapes of estimated trade-off curves are nearly logarithmic and the trends do not vary significantly between different equity reference distributions. Hence, if an equity score close to the cost minimizing scenario (scenario 2) is chosen, the cost increase is not significant. However, the control cost will increases for lower target of equity scores.

The salinity control allocation framework developed in this paper is not limited to the salinity problem in the UCRB only, but can be applied to other water resources and environmental management problems such as effective allocation of various pollutant control responsibility or water supply. The important outcomes of this study are that
establishment of organized policies in consideration of not only the cost but also equity measures which represent the interests of stakeholders and decision-makers.

LITERATURE CITED


Hayes, B. R., 1995. Geomorphic and Climatic Controls on Streamflow, Sediment, and


Conservation Foundation, Washington, D.C.


Table 4-1. Equity scores from minimizing optimization and back calculation for the 100% salinity control target of 657,900 tons per year in 2011, and corresponding back calculation using the peer reference distribution.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Equity Criteria</th>
<th>Average Equity Scores</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Control Cost</td>
<td>Possible Max. Control Amount</td>
</tr>
<tr>
<td>1</td>
<td>0.0689</td>
<td>0.3095</td>
</tr>
<tr>
<td>2</td>
<td>0.0288</td>
<td>0.3619</td>
</tr>
<tr>
<td>3</td>
<td>0.0288*</td>
<td>0.3619</td>
</tr>
<tr>
<td>4</td>
<td>0.0541</td>
<td>0.2445*</td>
</tr>
<tr>
<td>5</td>
<td>0.0674</td>
<td>0.4274</td>
</tr>
<tr>
<td>6</td>
<td>0.0339</td>
<td>0.3627</td>
</tr>
</tbody>
</table>

*Equity scores with star are optimized values. Other scores are back calculated from the optimization result of each scenario.
Table 4-2. Equity scores and corresponding annualized costs for 100% salinity control
target of 657,900 tons per year in 2011. Minimum and maximum equity scores are
estimated from comparisons among equity scores calculated by optimization and back
calculation for each equity criteria.

<table>
<thead>
<tr>
<th>Equity Reference Distribution</th>
<th>Equity Score</th>
<th>Scenario*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Peer</td>
<td>Optimized</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>0.0689</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>0.6087</td>
</tr>
<tr>
<td></td>
<td>Annualized cost</td>
<td>17.84</td>
</tr>
<tr>
<td></td>
<td>($\times 10^6$)</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>0.0522</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>0.4584</td>
</tr>
<tr>
<td></td>
<td>Annualized cost</td>
<td>17.84</td>
</tr>
<tr>
<td></td>
<td>($\times 10^6$)</td>
<td>-</td>
</tr>
<tr>
<td>Attribute</td>
<td>Minimum</td>
<td>0.0778</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>0.4544</td>
</tr>
<tr>
<td></td>
<td>Annualized cost</td>
<td>17.84</td>
</tr>
<tr>
<td></td>
<td>($\times 10^6$)</td>
<td>-</td>
</tr>
</tbody>
</table>

*Scenario 1 – distribution based on percentage irrigated land; Scenario 2 – minimum cost solution; Scenarios 3 through 6 - minimizing equity score with control cost, maximum possible salinity control quantity, irrigated land, and agricultural net income, respectively.
Table 4-3. Equity scores and the corresponding annualized costs using the peer equity reference distribution for different control targets from 100% target of 657,900 tons per year in 2011.

<table>
<thead>
<tr>
<th>Control Target</th>
<th>Equity Score</th>
<th>Scenario*</th>
</tr>
</thead>
<tbody>
<tr>
<td>75%</td>
<td>Optimized</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>0.0548</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>0.6087</td>
</tr>
<tr>
<td></td>
<td>Annualized cost ($×10^6)</td>
<td>12.44</td>
</tr>
<tr>
<td>50%</td>
<td>Optimized</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>0.0390</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>0.6087</td>
</tr>
<tr>
<td></td>
<td>Annualized cost ($×10^6)</td>
<td>7.67</td>
</tr>
<tr>
<td>37%</td>
<td>Optimized</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>0.0299</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>0.6087</td>
</tr>
<tr>
<td></td>
<td>Annualized cost ($×10^6)</td>
<td>5.44</td>
</tr>
</tbody>
</table>

*Scenario 1 – distribution based on percentage irrigated land; Scenario 2 – minimum cost solution; Scenarios 3 through 6 - minimizing equity score with control cost, maximum possible salinity control quantity, irrigated land, and agricultural net income, respectively.
Figure 4-1. Physical description of the Upper Colorado River Basin showing areas of irrigation and predicted incremental salinity load of each watershed in 2011.
Figure 4-2. Cost function for salinity control in the UCRB developed using data from USDA (US Department of the Interior, 2011).
Figure 4-3. Distribution of salinity control responsibilities across 59 watersheds in the UCRB using SPARROW simulation results of 2011. The boxes are showing interquartile ranges with medians at notches. Whiskers are showing the most extreme values that are not outliers, and were drawn with the maximum whisker length of 1.5.
Figure 4-4. Spatial distribution of salinity control responsibilities for selected scenarios using the peer equity reference distribution in the year 2011; (a) scenario 1 - base
solution, (b) scenario 2 - cost minimization, (c) scenario 5 - minimizing equity score for irrigated lands, (d) scenario 6 - minimizing equity score for net agricultural income.
(d) Scenario 6
Equity for net ag. income

Salinity control
(1000 tons/yr)

- 0 - 5
- 5 - 10
- 10 - 15
- 15 - 20
- 20 - 25
- 25 - 30
- 30 - 40
- 40 - 50
- 50 - 60

North America Albers Equal Area Conic Projection, NAD 1983
Figure 4-5. Temporal variation of salinity control responsibilities across the UCRB using the peer equity reference distribution and 37% of total control target for each year; (a)
2011, (b) 2004, and (c) 2002.
Figure 4-6. Histograms showing the number of watersheds and the corresponding salinity control responsibilities from scenario 2 using the peer equity reference distribution and 37% of the total control target for each year.
Figure 4-7. Trade-off curves between cost efficiency and equity score using equity for irrigated land area (or scenario 5) for 100% salinity control target in 2011.
CHAPTER 5

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

This chapter summarizes the key findings from each component of the integrated framework developed in this dissertation to achieve the overall goal of managing salinity issues in the Upper Colorado River Basin, and provides comprehensive conclusions and recommendations for further study.

SUMMARY

*Analysis of Salinity Sources and Transport: Modeling, Calibration, and Uncertainty*

The SPARROW salinity model in the Upper Colorado River Basin was extended to the recent years in Chapter 2, by applying estimates of evapotranspiration from the modified complementary method, NLCD 2006 for land cover and irrigated lands, precipitation, and salinity observations. Since the existing numeric criteria have been set along the Lower Colorado River and there is no criterion in the Upper Colorado River, a representative criterion at the outlet of the UCRB was suggested from an annual flow weighted average salinity concentration in 1972. The extension of the SPARROW salinity model was conducted from 1999 to 2011 using three calibration methods. This study suggested that calibration for the individual year was the best method because the accuracy of the calibration results was highly based on physical and statistical reasons. The watershed ranking scheme was proposed considering uncertainty by 1,000 iterations of resampled bootstrapping. Uncertainty played an important role in ranking watershed as the use of deterministic results only can mislead information in selection of vulnerable
watersheds to salinity.

Water Quality Monitoring Network

The number of monitoring stations in the UCRB is in steep decline due to financial issues. The decreasing trend of monitoring affects modeling and management directly because of increasing model uncertainty. Therefore, establishing effective monitoring network within limited budget is of great importance. As an index of effectiveness, station ratio, which is represented by relationship between the number of monitoring stations and the incremental water quality load, was proposed. By applying the station ratio and the spatially distributed water quality data (i.e. SPARROW salinity simulation results in this research), the number of monitoring stations in the individual watersheds can be estimated for each target station ratio. Scarcity or redundancy of each watershed in the existing salinity monitoring network was determined by the station ratio based analysis. From the results of Chapter 3, target SR of 25 or greater is recommended for salinity monitoring in the Upper Colorado River Basin using 2011 data. The developed decision-making methodology for an effective water quality monitoring network can also be applied to other basins or other water quality measures.

Cost-Equity Considerations in Salinity Management

A decision-making framework for the allocation of water quality control responsibility was developed in this research. Although the plan of implementation has been established and implemented to reduce salinity in the Colorado River Basin, the selection of location and the control amount is not explicitly studied. Salinity control in irrigated lands is simple and straightforward compared to public lands. However, controls
in private irrigated lands may face conflicts between stakeholders. The methodology
developed in this research considered equity among stakeholders as well as cost. Control
cost, irrigated land area, agricultural income, and possible maximum salinity control
quantity were used as equity criteria. From the allocation analysis in the Upper Colorado
River Basin, very similar results were produced for cost minimization and equity
maximization for the salinity control cost showed. Results were produced that provided
the low cost and good equity scores, indicating the conflicts for the control cost among
stakeholders can be minimized. While these scenarios related to control cost tried to
distribute control quantity equally, allocation using equity for maximum control quantity,
irrigated land area, or agricultural income resulted in large amount of salinity control in
small number of watersheds. The shape of the trade-offs curves between cost efficiency
and equity score formed nearly logarithmic, therefore, the marginal cost to increase
equity scores near low equity scores was not significant while the marginal cost increased
with better equity scores.

CONCLUSIONS

This dissertation describes an overall decision-making framework for water
quality management in a large basin, and demonstrates its application to salinity
management in the Upper Colorado River Basin. The salinity problem in the Colorado
River Basin has long been a serious concern for the United States and Mexico due to
release of the saline ions from the geologic materials to the Colorado River water by the
natural weathering and anthropogenic activities. Since the major source of the saline river
water is from nature, the increase of salinity and the consequential socioeconomic
damages are inevitable. Even though the efforts on salinity mitigation in the Colorado River Basin have worked effectively so far, the salinity is likely to exceed the numeric criteria again without further salinity control plans. Therefore, this dissertation developed decision-making methodologies to improve modeling salinity and to establish salinity control plan of implementation. The contributions from this dissertation are listed below.

1. The limitations due to lack of data on SPARROW salinity model were overcome, and the model simulation is able to be continued in the future using readily available observation datasets.

2. Comparison of the different calibration methods and consideration of uncertainty improved the prior salinity simulation results.

3. From the station ratio based analysis, water quality managers can investigate scarcity or redundancy of the existing monitoring network, and alter the network with the variations in their monitoring budget.

4. Water quality managers can organize salinity control policies based on not only the control cost but also equity among the interests of stakeholders and decision-makers from the allocation strategy developed in this dissertation.

5. The decision-making frameworks for monitoring network and allocation strategy developed in this dissertation can be extended to the other basin or other water quality measures.

RECOMMENDATIONS

Several potential extensions or limitations of the research developed in this dissertation are possible as follows.
1. Development of a transient SPARROW model can provide better understanding than the individual year calibration method suggested in this dissertation. However, monitoring sites have not been operated consistently, and changed from year to year. This limitation prevents the development of a single transient SPARROW model and the corresponding analysis of variations of parameter coefficients.

2. The analysis about water quality monitoring network effectiveness based on station ratio cannot be applied to a combination of two or more water quality parameters directly. Further study is required to understand how the multiple water quality parameters can be accommodated in the establishment of an overall monitoring network. In addition, this methodology is based on watershed scale, so that the exact location of the proposed monitoring station cannot be provided.

3. The allocation strategy considering cost and equity was applied to the controls by irrigated lands in the Upper Colorado River Basin only. Although salinity controls in irrigated lands are more practical and effective than in public lands, salinity control in public lands should be considered eventually.
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SELECTED TECHNICAL REPORTS

Working Design of Construction Documents for Channel Improvement of Pungyoungjeong-cheon(river), Gwangju Metropolitan City, South Korea, 2008

Development of Master Plan for River Improvement of Joryoung-cheon(river), Anseong-Si, Gyeonggi-Do, South Korea, 2007

Development of Master Plan for River Improvement of Suwon-cheon(river), Wanju-Gun, Jeollabuk-Do, South Korea, 2007

Working Design of Construction Documents for Channel Improvement of upper Miho-cheon(river), Daejon Regional Construction Management Administration, Ministry
Working Design of Construction Documents for Environmental River Restoration of Namwon Area, Igsan Regional Construction Management Administration, Ministry of Construction and Transportation, South Korea, 2007

Development of Master Plan for River Improvement of Seokgok-cheon(river), Gwangju Metropolitan City, South Korea, 2006

Development of Master Plan and Detailed Design for River Restoration of Gaeumjeong-cheon(river), Changwon-Si, Gyeongsangnam-Do, South Korea, 2006

Development of Master Plan for River Improvement of Banwol-cheon(river) Watershed, Gyeonggi-Do, South Korea, 2006

Development of Master Plan for River Improvement of Gumi-cheon(river), Gumi-Si, Gyeongsangbuk-Do, South Korea, 2006

Working Design of Construction Documents for River Improvement of Mangyeong Bank, Igsan Regional Construction Management Administration, Ministry of Construction and Transportation, South Korea, 2006

Working Design of Construction Documents for River Improvement of Dongjin Bank, Igsan Regional Construction Management Administration, Ministry of Construction and Transportation, South Korea, 2006

Working Design of Construction Documents for River Bank Improvement of National River, Wonju Regional Construction Management Administration, Ministry of Construction and Transportation, South Korea, 2005

Development of Master Plan for River Improvement of Gwangju-cheon(river), Gwangju Metropolitan City, South Korea, 2005

Development of Master Plan for River Improvement of Bongseongpo-cheon(river) Watershed, Gyeonggi-Do, South Korea, 2005

Working Design of Construction Documents for River Bank Improvement of Upper Tamjin River, Igsan Regional Construction Management Administration, Ministry of Construction and Transportation, South Korea, 2004

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Development of Master Plan for River Improvement of Banbyeon-cheon(river) and Jangpa-cheon(river), Gyeongsangbuk-Do, South Korea, 2004
Development of Master Plan for River Improvement of Maehwa-cheon(river), Gyeongsangbuk-Do, South Korea, 2004
Assessment of Impacts due to the Development of Residential Area, Yongin Guseong District, Korea Land and Housing Corporation, South Korea, 2004
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