ESTIMATING THE SPATIAL DISTRIBUTION OF SNOW WATER EQUIVALENT AND SIMULATED SNOWMELT RUNOFF MODELING IN HEADWATER BASINS OF THE SEMI-ARID SOUTHWEST

by

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DEDICATION

This dissertation is dedicated to all those who could, but did not know it and were never encouraged and to those who thought they could not, but someone encouraged them forward.
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ABSTRACT
The spatial distribution of snowpack in relation to snow water equivalent (SWE) and covered extent is highly variable in time both seasonally and interannually. In order to assess basin water resources, SWE must be distributed to areal estimates. This spatially distributed SWE connects the point scale to the larger scale of the basin (i.e. macroscale), requiring a combination approach of statistical interpolation techniques and snowpack extent constraint from remote sensing. This research connects those multiple spatial scales and applies the combined remote sensing and ground-based SWE products in a hydrologic model setting to aid in improving streamflow forecasting in the mountainous terrain of snowmelt-dominated basins, a current modeling gap. Four specific advancements were achieved: 1) a comprehensive assessment of spatial distribution techniques in interpolating point snow water equivalent (SWE) measurements at snow telemetry (SNOTEL) stations to the macro-scale was made and an optimal technique for distributing SWE on this scale was obtained; 2) differences between two major data sources of SWE (SNOTEL and snowcourse) were quantified for both point-scale variability and interpolated macro-scale variability to determine spatial and temporal differences in data sources for dry, average and wet years to better inform water resources management applications; 3) basin-scale estimates of ground-based SWE and snow covered area (SCA) from remote sensing were evaluated relative to equivalent fields calculated by a hydrologic model and the effect of assimilating the remote sensing products into the model were investigated; and 4) in the context of (3), improvements were made in macro-scale SCA estimates through both a canopy correction and a low
pass statistical filter in an effort to correct for the relatively low resolution of remotely sensed estimates.
1. INTRODUCTION

Seasonal snow cover is a small fraction of global fresh water stores, but its influence on the hydrologic landscape is large. The snow physical properties of depth, density and water equivalent (SWE) are most important to hydrologists (Maidment, 1993). Water content, or SWE, of seasonal snowfall is important for water managers, because the resulting melt fills reservoirs (surface and groundwater), controlling the amount of water available for uses such as irrigation, power generation and personal use (Dunne and Leopold, 1978). SWE is particularly important in mountainous regions where as much as 95% of total flow can result from snowmelt runoff (Shafer et al., 1982). Therefore, remote measurement of the extent, in terms of snow-covered area (SCA), and water volume, in terms of SWE, are important for runoff assessment and water management (König et al., 2001).

Current operational snowmelt runoff forecasts are based on empirical relationships, aggregating at least 20 years of data, regressing SWE values from snowcourse or snow telemetry (SNOTEL), precipitation, soil moisture and observed streamflow data. These are therefore, not suited for forecasting extreme events, which are of keen interest to water management. Satellite snow measurements have shown that SCA has decreased (Robinson, 1999), while recent studies have tied an increase in global mean air temperature to changes in the accumulated amount of snow through snowcourse observations (Mote, 2003) and the subsequent timing of spring melt (Dettinger et al., 2004). Additionally, SWE has shown similar trends with less occurring at lower elevations (Johnson et al, 1997).
Snow cover in the southwestern United States has also been connected to climate regimes such as the North Atlantic Oscillation (NAO) (Gutzler and Rosen, 1993), to regional phenomena such as summer time monsoonal activity (Gutzler and Preston, 1997) and is known to be potentially sensitive to climate change in the broader sense of water resources (McGinnis, 1997). Therefore, increased understanding of the spatial and temporal distribution of both SWE and SCA are increasingly vital for operational purposes. As anthropogenic sources contribute to climate change, seasonal snow cover is affected, leading to changing dynamics of streamflow in terms of timing and magnitude.

The physical processes governing snow distribution (e.g. wind, sublimation, topography, vegetation, etc.) are widely known, and considerable effort has focused on algorithm development to parameterize those processes. Variability of that distribution has been studied at three principal scales (Goodison, 1981): Macro-scale (~$10^5$ km$^2$); Meso-scale (~1 km$^2$); Micro-scale or point (~1 m – 100 m). In this dissertation the macro-scale and meso-scale are considered as the basin scale. Depending on the scale of interest, different techniques have been used to acquire or estimate snow amounts (e.g. SCA and SWE) and then distribute those estimates onto a larger scale. The remaining sections in this chapter are designed to highlight the history of SWE measurement types used in this study and issues related to those measurements (section 1.1). The current state of hydrologic modeling in regard to snowmelt estimation is then described (section 1.2).
1.1 SWE Estimation Overview

SWE is defined as the vertical depth of water that would be obtained by melting snow (Goodison, 1981), the product of the depth of snow and the specific density of that snow using the expression

\[ \text{SWE} = 0.01d_s \rho_s \] (1)

in which SWE is in mm when depth, \(d_s\), is in cm and depth-averaged density, \(\rho_s\), is in kg/m\(^3\) (Gray and Prowse, 1993). Many techniques for estimating SWE exist, based on the scale of measurement. The discussion will be limited to techniques associated with this dissertation and will progress from measured estimates at the micro-scale, or point, to meso-scale and macro-scale estimation from an approach that combines ground-based estimates and remote sensing.

Snow surveys, or snowcourses, have been conducted in an organized fashion since the 1930’s. Each snowcourse consists of approximately 10 stations marked by stakes to which the observer can return periodically, usually once or twice a month in the snow season (Dunne and Leopold, 1978). A more detailed description of site selection and procedural details is given by Goodison et al. (1981).

At these snowcourses, the standard for gravimetric measurement is a hollow snow tube for sampling of a snow core during snow surveys in the field. Although many types of snow tubes exist they differ mainly by dimension of the coring tube. The most commonly used sampler for snow surveys in the United States is the Federal Sampler, for example. Snow tube samplers are usually made of 30 in. long aluminum tubes with an inside diameter of about 1.5 in. Sampling is executed by vertically inserting the tube into the snowpack until it reaches the ground, and then turning the tube to plug the snow at the
tube base. The tube, with sample, is weighed and then tared without the sample to calculate a difference and, therefore, SWE. Although many samplers have been accepted for use, studies have shown that both cutter design and sampler diameter are important in the accuracy of measuring SWE by this gravimetric technique (e.g. Freeman, 1965; Goodison, 1978; Work et al., 1965).

Snow pits estimate the vertical distribution of snowpack density and are considered to be the most accurate ground-based measure of SWE, albeit time-intensive. Samples are taken by 250 cm³ – 1L cutter (and then weighed) at regular intervals along a smoothed, excavated pit wall, recommended to be north-facing to avoid exposure to solar radiation inputs. Studies have examined the differences between various sizes of snow cutters (e.g. Farnes et al, 1982), indicating uncertainty increases as the density of the snowpack decreases and as the cutter size decreases.

In 1963 the United States Department of Agriculture (USDA) Soil Conservation Service began the installation of an automated network of snow telemetry (SNOTEL) sites, also known as snow pillows, which are now operated by the USDA National Resource Conservation Service (NRCS). They were implemented to replace the gravimetric measurements of SWE taken at manual snowcourses, specifically at locations for which snowcourses were observed to have high streamflow correlation. Snow pillows, filled with antifreeze solution, measure SWE. Accumulating snowpack forces antifreeze into a manometric column, recording an increase/decrease in SWE, which is equal to the increase/decrease of manometric height (Beaumont, 1965). Inaccurate measurements can be made due to instrumentation sensitivities and equipment issues such as ice bridging across the snow pillow (Goodison et al, 1981). Measurements
unrepresentative of the station locale occur from environmental factors such as snow drifting, wind scour or falling debris. Specific site location differences between snowcourse and SNOTEL that are co-located (i.e. measurements taken at the same location) may include differing accumulation patterns and aspect exposure, producing differential melt in the ablation period (Palmer, 1986).

The actual placement of SNOTEL sites was in a clustered pattern in which coverage of high elevations and low elevations was very sparse (Figure 1). Most sites are located in the middle elevation regions (2000 m - 3000 m); however, a major proportion of the total snow water volume is above 3000 m (figure 2), as calculated by statistical interpolation of point measurements. The placement of sites simply does not capture all areas of significant snow and may not accurately represent basin water resources. Appendix B addresses this issue further.

![Figure 1](image)

**Figure 1.** Frequency distribution of elevation and SNOTEL station locations in the Colorado River basin.
SNOTEL point data have been used in a variety of ways as ground-based SWE data to evaluate climate impact on the snowpack (e.g. Mock, 1996; Serreze et al, 1999) and model studies to update the state of snowpack (Carroll et al, 2001), for example. To connect these point-scale estimates to larger scales, statistical techniques have been employed in mountainous terrain where point estimates of SWE are more sparse or unavailable. Estimates are interpolated from point-measured SNOTEL SWE (e.g. Carroll and Cressie, 1996; Carroll and Cressie, 1997, Daly et al., 2000; Fassnacht et al., 2003, in Appendix A; Ling et al., 1995). Physiographic variables (e.g. slope, elevation, vegetation) also have been used to distribute SWE through binary regression trees (Balk and Elder, 2000; Elder et al., 1998, Erxleben et al, 2002; Molotch et al., 2004a) or through multi-variate regression of those variables (Fassnacht et al, 2003 in Appendix A). Multi-variate regression of physiographic variables has also been used in macro-scale climate data gridding (e.g. Solomon et al, 1968).
In most cases remote sensing data are used to acquire the hydrologic state of an area or hydrologically significant physiographic variables (Pietroniro and Prowse, 2002). In the case of snow cover, remote sensing data have been used to delineate the covered extent (i.e. SCA). Statistical interpolations of SWE require masking with remotely-sensed snow covered portions of the basin, as the interpolations may include estimation into snow-free areas. To assess large areas with daily resolution, visible/near infrared sensor satellites such as AVHRR, Landsat Thematic Mapper (TM), or the MODerate resolution Imaging Spectrometer (MODIS) must be used (Cline et al, 1998; Fassnacht et al., 2003, Klein et al, 1998; Maurer et al, 2003; Molotch et al, 2004b). However, there are common problems of estimating snow under clouds and of mixed pixels (König et al., 2001). Recent advances have been made in estimation under clouds through iterative split-and-merge clustering, combined with dynamic cluster labeling to segment imagery (Simpson et al, 1998), and by applying accumulated degree day approaches (e.g. Molotch et al., 2004b) to constrain SWE, independent of any solar illumination issues. Visible/infrared sensors do not allow for direct measurement of SWE, but microwave wavelengths do. Direct satellite measurement of SWE is not studied in this dissertation. A review of techniques can be found in a Canadian study by Bernier et al. (1999) and more broadly in König et al. (2001).

Surface composition in terms of variables such as vegetation, SCA, and SWE changes with elevation as well as slope and aspect. Topography is determined as having a significant role in snow processes and snow characteristics (e.g. density and depth), evident in SCA patterns (Elder and Dozier, 1990; Elder et al., 1991; Blöschl et al., 1991). The problem, then, is characterizing these smaller-scale changes. That is, variables may
be spatially dynamic and introduce a mixed pixel issue in which multiple signatures or objects are present in a pixel, producing a mixed spectral signature at the satellite sensor. Common spectral un-mixing techniques such as density slicing, parallelepiped, maximum likelihood, principle components analysis (PCA) and band ratioing do not provide a foundation for quantifying SCA in any given pixel (Rosenthal and Dozier, 1996). Mixed pixel issues are not endemic to a specific sensor; however, the larger the pixel size, the larger the problem becomes, for there is a greater probability for heterogeneous signatures of surface types with increasing pixel size. In this dissertation, a canopy correction is applied to AVHRR-derived SCA in Appendix C to account for the mixed pixel issue in complex terrain.

1.2 Hydrologic Modeling Overview

Satellite-derived SCA is important for initializing snowmelt runoff models (e.g. Rango and Itten, 1976; Rango and Martinec, 1979; Martinec and Rango, 1981). Dozier (1989) reports an additional importance in estimating the radiation component of the surface energy balance. Snow-covered mountainous areas can be a large input to annual streamflow, but meso-scale and macro-scale hydrologic modeling of these regions is difficult due to poor data resolution (Davis and Marks, 1980) and terrain effects that limit remote sensing techniques. In snowmelt-dominated basins, such as those in the southwestern United States, estimating the water resources in snow and then using that information for management purposes is critical to urban water supplies, agriculture, and wildlife. Due to the importance of snowmelt in these areas, much effort has been focused on model development. A majority of process-level models have dealt only with accumulation and melt (e.g. Anderson, 1968; Blöschl et al, 1991; Rango and Martinec,
Rango and Martinec (1994), for example, review seven snowmelt runoff models, but they do not model the entire water balance, only that from snow.

Snow algorithm research also has been directed towards applications in land surface models. Algorithm development has included snow processes such as blowing snow transport, sublimation, forest canopy interception, albedo decay of snow, and soil heat flux (Pomeroy et al., 1998). Further, snow process algorithms are important for global circulation models (GCM’s) since snow-climate feedbacks have been established (Cess et al., 1993; Thomas and Rowntree, 1992; Randall et al., 1994; Karl et al., 1993). Development has focused on parameterizing the intricate relationship of energy balance and snow within forested areas. Furthermore, while land surface models have been used as an interface to global climate models (GCMs), they also may be used as an interface in coupled atmospheric and hydrologic models.

Although process-based snowmelt modeling has steadily improved, snowmelt-modeling is commonly a weakness of hydrologic models (Walter et al, 2005) due to use of temperature-index or degree-day snowmelt relationships. Hydrologic models simulate streamflow from snowmelt runoff to varying success in mountainous regions. The soil water assessment tool (SWAT) model, for example, does not perform well in mountainous basins as reported by Arnold et al. (1999), however, Fontaine et al. (2002) modified the model by improving the parameterization of the snow processes routines. The precipitation-runoff modeling system (PRMS) model (Leavesley et al., 1983) is similar to SWAT, because it not only addresses the accumulation and melt of snow but it also addresses total water budgets. It may be applied over a large region, but is limited by temperature and precipitation parameterization data in mountainous terrain over those
large areas. Due to limited climate forcing data, it is reasonable to directly measure the snowpack variables (i.e. SCA and SWE) estimated from that climate forcing instead of simulation with sparse data.

The study in Appendix C aims to fill this gap. Modeled snowpack estimated from climate data and a snowpack developed by a combination of remotely sensed SCA and ground-based SWE are compared. Snowmelt is simulated in the PRMS hydrologic model to evaluate the measured estimate of SCA and SWE with the modeled estimates.
1.3 Dissertation Format

The format of this dissertation includes a chapter on the Present Study, which briefly summarizes the findings of the three manuscripts included in the Appendices (A-C). Appendix A is a journal paper that was published in Water Resources Research, August 2003, examining several statistical techniques for interpolating SNOTEL point data on the macro-scale. Appendix B is a manuscript “in review” to the Journal of Hydrometeorology, describing spatial data issues with co-located SNOTEL and snowcourse measurements in the Colorado River basin. Appendix C is a manuscript on assimilating distributed SCA (used in Appendix A) and SWE products (used in Appendices A and B) into a hydrologic model. It is in preparation for immediate submission to the Hydrological Processes journal.

Each paper, or manuscript, addresses at least one of the following main questions:

1) What is the spatial and temporal distribution of SWE over wet vs. dry years?

2) How important are differences at the small (point) scale and at the large (basin) scale when distributing snow information from a point measurement?

3) What is the impact of remotely sensed snow information on the state of hydrologic modeling?

This dissertation examines SWE at the point and distributed estimates from interpolation. To accomplish this task, three major scales of interest from different acquisition sources were combined. SWE data were examined at co-located SNOTEL and snowcourse sites and at the macro-scale using interpolation. An interpolated SWE product from SNOTEL point (~ 1-10 m) measurements was produced from a review of spatial distribution techniques for interpolation of ground-based SWE to the macro-scale...
scale ($10^3 – 10^5$ km$^2$). The SWE product was examined on a third scale by masking with the meso-scale (~1 km) SCA developed from AVHRR at the Regional Earth Science Applications Center (RESAC) at the University of Arizona and compared against a modeled snowpack estimated from climate forcing data of temperature and precipitation. Limited literature is available on SWE estimations over the macro-scale ($10^5$ km$^2$), and even less on the impact those estimates have in hydrologic models. This dissertation contributes to those knowledge gaps.
2. PRESENT STUDY

This section is divided into three components, represented as published, in review, and publishable journal articles in Appendices A, B, and C, respectively. Research on estimating the spatial distribution of snow water equivalent (SWE) is described first (Appendices A and B), then issues associated with SWE data sources (Appendix B) and finally an evaluation of measured SCA and SWE estimates against a simulated snowpack from a hydrologic model is described (Appendix C).

2.1 Summary of Paper #1 (APPENDIX A):
Snow water equivalent interpolation for the Colorado River Basin from snow telemetry (SNOTEL) data

This paper was published in the journal of Water Resources Research. (DOI:10.1029/2002WR001512, 2003) and is shown as the published form. The objective of this work was to assess statistical techniques for interpolating point SWE values to distributed area estimates over the macro-scale (~10^5 km^2). Inverse weighted distance and various regression, non-exact techniques, were assessed as interpolation methods for SWE in the Colorado River basin, southwestern United States. One-km pixel spacing was used for the gridding of SNOTEL values, for the years 1993, 1998, and 1999, which on average represented higher than average, average and lower than average snow years. Due to the terrain effects, the regression techniques (hypsometric elevation and multi-variate physiographic parameter) were found to be superior to the weighted distance approaches (inverse distance weighting squared, and optimal power inverse distance weighting). A regression detrended inverse weighted distance method was developed for the hypsometric and multi-variate techniques, in order to preserve the point SNOTEL
data. Based on root mean square error analysis and estimates of SWE volumes in different elevation zones for the entire basin and for sub-basins, the elevation detrended method with a point-by point regression was found to be the most appropriate technique. Various search radii and anisotropies of the search ellipse were tested with the hypsometric method, producing only small differences in the root mean square error and SWE volumes.

This research has contributed to the field of hydrology by connecting point scale measurements of SWE to the larger basin scale \((\sim 10^3 - 10^5 \text{ km}^2)\), or macro-scale, through a review of statistical, spatial interpolation techniques. The optimal technique for distributing SNOTEL SWE is used in Appendixes B and C.

2.2 Summary of Paper #2 (APPENDIX B):
A comparison of snow telemetry (SNOTEL) and snowcourse measurements in the Colorado River Basin

This manuscript is in review at the Journal of Hydrometeorology. The objective of this work was to quantify spatial and temporal differences over differing water years (dry, average, wet) between SNOTEL and snowcourse data at the point \((\sim 1 - 10 \text{ m})\) and basin scale \((\sim 10^3 - 10^5 \text{ km}^2)\), or macro-scale, to better inform applications such as water resource management regarding issues of using either data source for operations or modeling. Temporal and spatial differences in snow-water equivalent (SWE) at 240 snow telemetry (SNOTEL) and 500 snowcourse sites and a subset of 93 co-located sites were evaluated by examining the correlation of site values over the snow season, interpolating point measurements to basin volumes using hypsometry and a maximum snow extent mask, and by variogram analysis. The lowest correlation at a point \((r = 0.79)\)
and largest interpolated volume differences (as much as 150 mm of SWE over the Gunnison basin) occurred during wet years (e.g. 1993) (Figure 3).

**Figure 3.** March 30, 1993 hypsometrically interpolated SWE (normalized by basin area) using various combinations of data, by sub-basin.

Interpolated SWE values based on SNOTEL versus snowcourse were not consistently higher or lower relative to each other when considering comparison of results at different interpolation scales (Colorado versus smaller sub-basins). Interpolation RMSE was comparable for both data sets, increasing later in the snow season. Snowcourses correlate over larger distances and have less short-scale variability than do SNOTEL sites, making them more regionally representative. Using both data sets in hydrologic models will
provide a range of predicted streamflow, which is potentially useful for water resources management.

This research has contributed to the field of hydrology by determining spatial and temporal differences among co-located measurements of SWE at both the point-scale and basin scale from two different data sources (SNOTEL and snowcourse). Previous comparisons only have been made at the point and only for small subsets of the data sources. Therefore, differences between total basin resources from either data source have not been assessed to better inform water management applications.

2.3 Summary of Paper #3 (APPENDIX C):
Streamflow Estimation from Hydrologic Model Updates of Remotely Sensed Snow Information in Snowmelt Dominated Basins

This manuscript is in preparation for submission to the Eastern Snow Conference special issue of the Hydrological Processes journal. The objective of this work was to evaluate the NASA Southwest Regional Earth Science Applications Center (RESAC) fractional SCA and snow water equivalent (SWE) products against a simulated snowpack from temperature and precipitation in a hydrologic model. The SWE product was developed in Appendix A and revisited in Appendix B.

The USGS Precipitation Runoff Modeling System (PRMS) hydrologic model was used to evaluate experimental, gridded, 1-km² snow covered area (SCA) and snow water equivalent (SWE) products for two headwater basins in the Rio Grande and Salt River drainages in the Southwestern United States, developed by the Southwest Regional Earth Science Applications Center (RESAC). The SCA product was the fraction of each 1-km² pixel covered by snow and was derived from NOAA Advanced Very High Resolution
Radiometer imagery. The SWE product was developed by multiplying the SCA product by SWE estimates interpolated from National Resources Conservation Service Snow Telemetry (SNOTEL) point measurements for a six-year period (1995-2000). Measured SCA and SWE estimates consistently underestimated modeled SCA and SWE estimated from temperature and precipitation. Differences between modeled and measured snow were different for the accumulation period vs. the ablation period and dependent on elevation. Greatest difference occurred in the relatively complex terrain of the Grande as opposed to the Black (Figure 4).

**Figure 4.** Average SWE differences ± standard error for the Black before April 1 (a) and after April 1 (b); and for the Grande before April 1 (c) and after April 1 (d). Values were calculated by subtracting the measured value from the model (base) value for each time step an update is available, expressed as the average value per 1-km$^2$ pixel within each 250-m elevation zone.
Assimilating RESAC snow fields into the PRMS model reduced model performance by removing water in both basins and the negative impact accumulated through the season (Figure 5). Hydrologic models incorporating RESAC SCA and SWE must be recalibrated to adjust to measured inputs.

![Graphs showing discharge and SWE change for Black and Grande during 1998.](image)

**Figure 5.** Discharge for the Black and Grande during 1998. Simulations were the same as Figure 7. Cooperative stations used for calibration provided climate data. Precipitation values represent events > 0.1 inches accumulation and updates shown had less than 50% cloud in the measured SCA AVHRR scene. SWE change was calculated as measured minus modeled so that negative values indicate a loss of SWE from the catchment.

This research has contributed to the field of hydrology by investigating the effect of incorporating basin scale distributed estimates of SWE, constrained by remotely sensed SCA (and vegetation correction improvement of that product) into a hydrologic model. Hydrologic models typically do poorly in mountainous terrain due to inadequate forcing.
data. Although the inconsistency between the remote sensing data and PRMS proved problematic in the present study, updating the model with remotely-sensed snowpack remains a promising technique to estimate model snow states over large regions where forcing data may be sparse.

Together, the studies in Appendixes A, B, and C explore spatial and temporal differences in SWE at several spatial scales from the point-scale to the macro-scale. Statistical interpolation techniques improved spatial estimates of SWE at the macro-scale and point data sources were evaluated at both the point-scale and the macro-scale to better inform water resources applications of the implications of using either source. Remote sensing of SCA at the meso-scale and ground-based techniques of (SWE) at the macro-scale, scaled up from the point-scale, were combined to refine spatially distributed SWE estimates compared with the snowpack state of a hydrologic model which simulated snowpack from climate data. Further improvements to the combined SCA and SWE product were achieved by a canopy correction that addresses the mixed pixel signatures of AVHRR satellite resolution in heterogeneous terrain. These are all critical steps towards enabling hydrologic models to better estimate snow processes on the large scale in mountainous terrain where climate forcing data are more limited but where model simulations of snowpack mass balance are necessary to estimate runoff.
3. REFERENCES


*Proceedings of the 69th Annual Western Snow Conference*, 1-14.


APPENDIX A: SNOW WATER EQUIVALENT INTERPOLATION FOR THE COLORADO RIVER BASIN FROM SNOW TELEMETRY (SNOTEL) DATA
Snow water equivalent interpolation for the Colorado River Basin from snow telemetry (SNOTEL) data

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Abstract

Inverse weighted distance and regression non-exact techniques were evaluated for interpolation methods of snow water equivalent (SWE) across the entire Colorado River Basin of the western United States. A 1-km spacing was used for the gridding of snow telemetry (SNOTEL) measurements, for the years 1993, 1998, and 1999, which on average represented a higher than average, average and lower than average snow years. Due to the terrain effects, the regression techniques (hypsometric elevation and multi-variate physiographic parameter) were found to be superior to the weighted distance approaches (inverse distance weighting squared, and optimal power inverse distance weighting). A regression detrended inverse weighted distance method was developed for the hypsometric and multi-variate techniques, in order to preserve the point SNOTEL data. Based on root mean square error analysis and estimates of SWE volumes in different elevation zones for the entire basin and for sub-basins, the elevation detrended method with a point-by point regression was found to be the most appropriate technique. Various search radii and anisotropies of the search ellipse were tested with the hypsometric method, producing only small difference in the root mean square error and SWE volumes.

key words: snow water equivalent, SNOTEL, spatial interpolation, Colorado River
Introduction

Approximately 70-80 percent of the total annual runoff in the western United States (U.S.) originates as mountainous snowmelt [Doesken and Judson, 1996]. Interannual variability of snow accumulation and melt can have dramatic impacts on western water interests. The timing of available water is critical, necessitating improved runoff forecasts from water supply and flood forecasters. While snow is not considered important by the general populace in the semi-arid southwestern U.S., Osterberg [1993] wrote that snow has a subconscious influence on the modern populations of the western U.S.; snow, even when not directly affecting an environment, builds to the allure of the wild and rugged nature of the west.

To estimate snow quantities for the western U.S., snow-covered area (SCA) maps are being derived from National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) satellite imagery [e.g., Daly et al., 2000] and snow water equivalent (SWE) maps from point measurements [e.g., Carroll, 1995]. The National Weather Service’s National Operational Hydrologic Remote Sensing Center (NOHRSC) produces binary (snow or no snow) SCA maps at a 1-km² resolution for the western U.S. [Carroll et al., 2001], while imagery fractional SCA maps are produced for the greater Colorado River Basin by the Southwest Regional Earth Science Application (RESAC) [Fassnacht et al., 2001a].

Statistical methods have been used to interpolate SWE for large areas where there is limited variation in topographic relief [Carroll et al., 1999], or for small basins in alpine terrain [Carroll and Cressie, 1997; Elder et al., 1998; Balk and Elder, 2000]. Interpolated SWE has been done using kriging [Carroll, 1995], elevation-detrended
kriging [Carroll and Cressie, 1996], or physiographic variables using binary regression trees [Elder et al., 1998; Balk and Elder, 2000]. The use of binary regression trees, especially when combined with residual kriging produced excellent results [Balk and Elder, 2000], however this method can be data intensive and seems best suited for smaller basins. Daly et al. [2000] used hypsometry-detrending to develop sub-basin regressions for SWE interpolation. The method has not used applied to a large watershed, such as the Colorado River, using regressions computed at each pixel. Additionally, the search criteria associated with such a regression has not been evaluated.

Multi-variate regressions of physiographic variables has been used for larger scale climate data gridding [Solomon et al., 1968; Daly et al., 1997; Seglenieks et al., 1999], but these have been limited to data of larger time steps, such as monthly climate normals, and these regressions have not been applied to large scale SWE interpolation.

Various data sources have been used to develop the spatial estimates, including snowcourse measurements, snow telemetry (SNOTEL) snow pillow measurements, airborne gamma measurements and local fine scale basin measurements. NOHRSC produces an operational SWE map for the entire U.S. [NOHRSC, 2002], but these images only represent the deviation from normal and not the actual SWE. To date, no historical time series of SWE imagery exists for large domains with highly variable topography.

Non-exact interpolation techniques calculate the value at a point without using the observed value at that point in the interpolation calculation. Point estimation procedures with this characteristic were desirable since exact methods such as kriging can not easily nor automatically consider selective data inclusion such as anisotropy in search radii for the distance weighting and hypsometric methods. The SNOTEL SWE dataset contains
some local fluctuation in the degree of anisotropy, and sample variograms using kriging appear isotropic because the local anisotropy undulations are smoothed out [Isaaks and Srivastava, 1989]. Exploratory variograms analysis of the SWE data indicated that kriging may be useful for localized areas of the study basin (e.g. mountain areas vs. foothills) but large-scale interpolation using this method loses the anisotropy of SWE inherent to mountain range geographic orientation and topographic heterogeneity.

Kriging and cokriging, such as with elevation, have proven useful for smaller domains (eg. Carroll and Cressie, 1996; Carroll and Cressie, 1997), however the selection of a model to fit a variogram cannot easily be automated. Authorised variograms can be selected, but at present the seasonal and inter-annual variability in the SNOTEL basin across a large basin, such as the Colorado, are not known. Therefore automated fitting of an authorized variogram is uncertain.

In this study, three different types of statistical techniques for interpolating basin-wide SWE are compared to determine an automated, robust approach for estimating the large-scale spatial distribution of water volume at a 1-km² resolution. This resolution is used so that the SWE maps are at the same resolution as the AVHRR-derived fractional SCA time series produced by RESAC. The techniques are: distance weighted methods (inverse distance squared and optimal weighted distance), regression methods (hypsometric and multi-variate physiographic), and detrended regression-inverse weighted distance methods (with regression from both the hypsometric and multi-variate physiographic approaches). The robustness of each approach is examined from the root mean square errors. The SWE volumes over the Colorado Basin and in three sub-basins are compared for different elevations and while ground data were not available, the true
magnitudes can be surmised. Since a moving search radius can be used for computation around each grid block, the impact of different search radius sizes and shapes is examined.

**Study Area**

The Colorado River Basin of the southwestern United States is over 1300 km long and up to 800 km wide. A majority of the snow within the basin is found in the Upper Colorado Basin (Figure 1), which has a drainage area of 277,000 km², an elevation range of 975-4260 m and an average elevation of 2150 m. The Lower Colorado has a drainage area of 346,000 km², with an elevation range of 0-3771 m and an average elevation of 1310 m. Almost 60% of the Upper Colorado Basin, but only 16% of the Lower Basin, is above 2000 m. The snow in the Lower Basin is located along the Mogollan Rim in eastern central Arizona, up through the Colorado Plateau approaching the Grand Canyon, and in western New Mexico. The focus of this paper is the entire Colorado Basin and three sub-basins: Gunnison (20,500 km²), San Juan (63,700 km²), and the Salt-Verde (35,100 km²) (Figure 1). The snowpack in the alpine areas of the Gunnison and San Juan follow the trends illustrated with the Lake Irene SNOTEL station (Figure 2a). The average snowpack in Arizona (Figure 2b) typically starts to accumulate a month later than mid-basin areas, is only a third as deep, peaks more than a month earlier, and is completely ablated up to two months earlier.
Data

Snowcourse measurements have provided biweekly to monthly SWE at up to 2000 sites in the western U.S. However, since SNOTEL stations are automated daily measurements of SWE (plus precipitation and temperature), these data are used in the analysis. SNOTEL data are currently available for more than 650 sites in the montane western U.S., with approximately 240 operated around the Colorado Basin since 1991 (see Serreze et al. [1999] for a description of the stations and the data).

SNOTEL sites measure daily changes in SWE, yet erroneous measurements can be made due to instrumentation sensitivities and equipment issues such as ice bridging across the snow pillow, or due to environmental factors such as snow drifting, wind scour or falling debris. To address data quality concerns, Serreze et al. [1999] compiled a set of quality control procedures for the SNOTEL data. This methodology was used to quality control the SNOTEL data. Specifically Serreze et al. [1999] implemented and performed the following to mask outliers and eliminate negative SWE values: stations with missing values for the first 15 days of the water year (October) were assumed to be indicative of delays in servicing and the entire year was deemed to have no data recording, daily SWE increments greater than 25.4 cm or consecutive days with increases and subsequent decreases each greater than 6.35 cm were deemed to have no data, monthly SWE decreases more than five standard deviations from the mean were deemed to be erroneous, and monthly SWE increases more than five standard deviations from the mean without a comparable extreme value for precipitation or a corresponding precipitation increment of more than three standard deviations were deemed to be erroneous. Where erroneous data were identified, all subsequent SWE measurements
were also considered no data, to eliminate the contaminating effect of an individual erroneous value. These same procedures were applied to the data used in this analysis.

From the ten years of SNOTEL record (1990-99), three years were chosen for this analysis. The selection was based upon representative above-average (1993), near-average (1998), and below-average (1999) snow years (Figure 2a and 2b).

**Methods**

*SWE Interpolation Methods*

Four main interpolation techniques were employed at a grid resolution of 1 km²: inverse weighted distance squared (IDW), optimal distance averaging (ODA), hypsometric (HYP), and multi-variate physiographic regression (MVR). As well, the hypsometric and multi-variate methods were combined with inverse weighted distance interpolation of the residuals, called detrended regression-inverse weighted distance techniques, and were assigned the acronyms HYP+IDW and MVR+IDW, respectively. Kriging was not used as results are similar to the distance weighting approaches, and the model fitting for the kriging semi-variogram cannot be easily automated.

Inverse distance weighting and optimal distance averaging are included in a suite of distance-weighting techniques. Weights of the interpolation function were based solely upon the distance between the sampling points and the point of interest. The weight of the sampling point was given by the inverse of the distance, taken to an exponential power; the power was 2 for IDW and was variable for ODA. The ODA technique searched for the optimal power between 0.5 and 4 by increments of 0.1. The
optimal power was defined by the power that produced the smallest mean absolute error for all the SNOTEL stations.

The hypsometric method regressed SWE with elevation, since SWE shows a strong positive relationship with elevation [Dingman, 1981]. The regression of SWE with elevation was based on station elevation, and applied to the gridding domain using a 1-km digital elevation model (DEM). Since regression relationships changed daily as meteorological factors impacted the snowpack, a new regression was calculated for each observation day. Only actively recording stations were considered in the regression calculation for each day, as some SNOTEL stations were not operated continuously.

A linear multi-variate regression was used between physiographic variables and SWE. Initially, each variable was assessed with respect to its relationship to SWE and the variable with the largest correlation selected. Subsequently the remaining variables were assessed individually, combined with the selected variable, and the optimal additional variable was added to the selected set. This procedure was repeated until the addition of new variables no longer increased the correlation coefficient by more than 0.01. This threshold was chosen as improvements less than this amount were deemed to be small. The final set of coefficients was recorded for each day when SWE was regressed. Twenty-seven physiographic variables and one forest variable (canopy density) were used in the analysis, as listed in Table 1 [see detailed description in Fassnacht et al., 2001b]. The variables were computed for a 1-km pixel based on a 100-m digital elevation model (DEM). A resolution of 1 km was used in the analysis. Five variables are station based: the 3 location coordinates (latitude, longitude, elevation), slope and aspect. The sine of the slope was used to normalize this variable, the sine of
aspect was used to yield the degree of northness, and the cosine of aspect was used to yield the degree of eastness. The normalized slope and two normalized aspect variables combine to yield a directional slope, i.e., gradients in the z, y, and x directions, respectively. Four different scales of directional slope were chosen: the local slope at 1 km, two footprint slopes, and a regional slope. The footprints were 3-km by 5-km area around each station or grid point offset to the west or the south; the footprints are used to determine on which side of the mountain that a station or grid block is located, i.e., as an indicator of windward versus leeward side, as this is very important for orographic precipitation. The regional slope is a 9-km by 9-km area centered around each station or grid point. Additional derived variables are based on Solomon et al. [1968], and include distance to ocean, barrier height (difference in height from the highest point between the ocean and the station), barrier distance, and shield height (cumulative elevation rise from the ocean to the station). A canopy variable was used since, in the western US, forests only grow in areas with sufficient precipitation, which for the Colorado Basin are higher elevations where coincidently a majority of the precipitation falls as snow. Canopy density was used as a surrogate for forest type, as forest type necessitates using a probability or logical regression. The canopy density was derived from 1-km AVHRR imagery, acquired from the U.S. Forest Service [2001], and developed as per Zhu and Evans [1992]. It turns out that canopy density was not an important variable in the regression (Table 1), likely since it is correlated with other variables [Fassnacht et al., 2001b]

The hypsometric regression and multi-variate linear regression approaches were combined with the inverse weighted distance gridding of the residual, called HYP+IDW
and MVR+IDW respectively. A linear regression relationship was computed and applied to the entire gridding domain. A regression residual was obtained at each station grid block. All residuals were regressed to a datum (5000 m) using a constant lapse rate (9.8 mm/km). From the common datum, the lapsed residuals were gridded using the inverse distance weighting squared technique. The gridded residual surface was then regressed to the basin surface and subtracted from the hypsometrically and multi-variate derived SWE surface. Both approaches preserved the SWE observation at each station. Different datums were tested and the choice of datum was not important. Daly et al. [2000] used the combination of hypsometry and IDW gridding of the residual, where one regression, i.e., a lapse rate and an intercept, was determined for each sub-basin of the headwaters of the San Joaquin and Sacramento Rivers in California. The HYP+IDW approach presented here used a moving search radius, with the hypsometric regression computed for each 1-km² grid block. The individual grid-block lapse rates were tested, but this use of many rates required lapse rate interpolation between stations which resulted in rounding errors. Different lapse rates for the entire study area were tested and their magnitude was found to be irrelevant, as long as it was +/- 5000 mm/km. This bound is a result of rounding errors associated with using a step slope, i.e., lapse rate.

**SWE Interpolation Search Parameters**

Five defined search radii were used (100, 200, 300, 400, 500 km). The radius determined the maximum distance for which to consider station influence, from a minimum of 2 stations to a maximum of 50 stations. Anisotropy in SWE variation was considered by using variable directional factors of one-third, one-half, two-thirds, unity, one-and-a-half,
two, and three. An anisotropy factor of unity indicated no directional influence, i.e., a circular search radius, while an anisotropy of one-third or three indicated an ellipsoid with the major axis being 3 times larger than the minor axis. The area defined by the search radius was maintained.

**Error Evaluation**

A weekly time step from December 29th to June 29th was used for each of the 3 study years. Weekly variation in SWE was limited and the value on the specific day was used in the interpolations. The time period was selected since in late December all SNOTEL sites had snow accumulated some snow, and by late June snow had ablated from almost all SNOTEL sites. This considers that accumulation is more uniform in space than ablation.

The station error was calculated from the difference of the station’s observed SWE and the estimate of SWE at the station without using particular station’s data. For each time step, the station errors were used to compute the root mean-square error (RMSE). The RMSE was computed for the different interpolation methods, data types, and search radius factors. The control used for comparing different data types and search radius parameters was the hypsometric interpolation using only SNOTEL data and an isotropic search radius of 200 km. The hypsometric method using a search radius of 1500 km uses all data to define a single regression equation for the entire study area. Hypsometry was used for these comparisons as there is a greater effect on SWE for anisotropy and search radii using this method than using weighted distance approaches.
A radius of 200 km was used due to the distribution of the data in certain areas, i.e., a smaller search radius would not find enough stations for interpolation in some locations. The combined regression-residual approaches (HYP+IDW and MVR+IDW) preserve the station values, so the station errors for these two methods are a function of their respective base methods, i.e., HYP and MVR.

**SWE Volume Estimates**

As a subsequent evaluation of the different interpolation methods, the distribution of SWE volumes across different elevation bands were compared. Water resources managers often use 500-ft (152-m) elevation bands for small to medium-sized basins [Fassnacht et al., 2001a]. The focus for this study was the Colorado River Basin, and 500-m elevation bands were used to define low, medium and high elevation zones. SWE interpolation extended into lower elevation areas where the occurrence of a substantial snowpack was unreliable. Therefore, the maximum snow extent, observed from a time series of satellite (AVHRR) SCA images from the 1998 and 1999 snow season, was used to define the possible snow covered areas. All SWE estimates outside the maximum snow extent were set to zero.

**Method Selection**

The most appropriate method for interpolating SWE for the entire Colorado Basin will be selected based on minimizing the RMSE and assigning the most adequate volume of SWE to different elevation zones across the basin and in sub-basins. The actual SWE volumes are unknown, but overestimations and underestimations are intuitive for the
different elevations, in particular, less snow at lower elevations and more snow at higher elevations. The errors associated with the SNOTEL data are unknown. However, for the purpose of the methods comparison, the SNOTEL point data will be assumed to be ground truth.

Results

For 1993, the optimal power was near 0.5 through early March then increased gradually to 1.3 in late April, after which the number of stations reporting snow dropped off and the optimal power decreased (Figure 3). The trend in the magnitude of the optimal power was consistent for the other two years.

Among the four non-residual methods, the hypsometric and multi-variate regression techniques had the lowest RMSE in all 3 years (Figure 4a-c), with weighted distance techniques exhibiting the poorest performance. Using all data with the hypsometric technique (HYP all data), yielded larger RMSE than when the 200-km search radius was used. The linear multi-variate regression technique performed slightly worse in terms of RMSE with (MVR+IDW) than without (MVR) the gridded residual. The average yearly RMSE and bias for the different methods is included in Table 2.

Without removing SWE estimates beyond the maximum snow extent, there is a significant difference between the inverse distance and regression interpolation techniques at lower elevations (Figure 5). The SWE estimates decreased substantially when clipped, and the difference between methods was less noticeable but still present at lower elevations. These data were shown for March 30, 1993 as this roughly when peak accumulation occurs over all elevations across the entire basin.
Examining the time series of SWE volumes per elevation zone, the largest difference in SWE volumes for the various interpolation techniques occurs in the mid-elevations later in the 1993 snow season (Figure 6a-d). As illustrated in Figure 5, the inverse weighted distance approaches (IDW and ODA) provide larger SWE volume estimates at lower elevations (Figure 6a-b) and smaller estimates higher elevations (Figure 6c-d). These patterns were also observed for 1998 and 1999. The trends in the SWE volumes were similar for the Gunnison sub-basin for 1993 (Figure 7a-d) and the two other study years. However, for the Salt-Verde sub-basin (Figure 8a-c), the multivariate technique produced results similar to the inverse weighted distance approaches, and hypsometry with all data yielded the largest SWE volumes during the ablation.

Increased search radii increased the RMSE for all study years, especially 1999 (Figure 9), as SWE increased. For March 30th, 1993, the differences in SWE were only observed at the lowest and highest elevations, where SWE volumes were small (Figure 10). Anisotropy had a limited effect on RMSE, primarily during March-April. The SWE differences from various anisotropies were larger at the lowest elevation and within 10% at the mid-elevations (Figure 11).

**Discussion**

The spatial variation of SWE increases as the snow season progresses. The plots of RMSE for each of the three study years (Figure 4a-c) illustrate that all errors increased with time until mid May, when the errors began to decrease. The errors increased with time as there is greater spatial variation in the rate and amount of accumulation as the snow season progresses. This variation becomes more significant when snowmelt begins
for some SNOTEL sites, which is late February in 1993 and 1998 and early January in 1999. The magnitude of the average grid block error corresponded with the increase in the optimal power (Figure 3), i.e., less reliance on data from further stations. Lag distance between stations becomes influential to SWE interpolation when the spatial variation in snowpack state is greatest. After May 27th, 17th and 23rd for 1993, 1998 and 1999, respectively, all stations are in an ablation phase, and RMSE and optimal power both decrease as the stations exhibit a same snowpack state. The average timing of the peak across the basin is mid-April for the three years. The SNOTEL stations throughout the Colorado basin are located at a variety of elevations and across all latitudes and thus the timing of accumulation, peak and ablation varies (eg. Figures 2a-b). As well, the snowpack is less continuous at lower elevations due to an earlier onset of melt. The earliest melt-out is March 29th, March 30th and February 9th, for the three years.

The differences in Figure 5 illustrated the impact of considering the maximum snow extent. Since the inverse weighted distance approaches do not consider topography, they produced substantially higher SWE volumes, especially at lower elevations, when not bounded by the maximum snow extent (Figure 5), and smaller estimates at the higher elevations (Figure 6a-d).

The weighted distance techniques do not account for variations in elevation (Figure 5). Precipitation is correlated directly with elevation [Dingman et al., 1988] and temperature inversely, thus SWE is directly correlated with elevation. The hypsometric regression method considers elevation, and the multi-variate regression considers this and other physiographic influences on SWE. Results from the regression techniques were similar, with the MVR illustrating slightly less error (Table 2), similar bias values (Table
2), and slightly lower SWE (Figures 6a-d). While this was consistent for the Gunnison sub-basins (Figure 7a-d), the MVR estimates were substantially larger than the HYP estimates for the Salt-Verde (Figure 8a-c) since the entire Colorado domain was used to generate the multi-variate regression. The physiographic properties of the Salt-Verde SNOTEL stations were similar to those in areas with more snow, i.e., more northerly locations, yet the snowpack is not as substantial and more of the snowpack had depleted in the southerly Salt-Verde. At the lowest elevation range, the MVR SWE was more consistent with the HYP SWE. Although computationally significant, multi-variate regression using a moving search radius, or at least sub-basin specific, should be investigated. Hypsometric interpolation with all data, i.e., a single hypsometric equation, produced the largest SWE volumes for the Salt-Verde Basin, illustrating the large-scale spatial differences in the SWE-elevation relationship and that a single regression does not capture basin-to-basin variations. The annual RMSE and bias are larger for the single hypsometric equation, compare to point by point interpolations (Table 2).

The regression detrended IDW methods (HYP+IDW and MVR+IDW) produce the most realistic results, given that station observations are representative, as SWE is preserved at the stations and regression residuals are distributed. The multi-variate residual technique provides the most physically based representation of SWE. Interpolated snow maps from the regression detrended techniques should compare to satellite-derived snow-covered area maps to examine differences in extent.

The representativeness of the SNOTEL data is also uncertain [Daly et al., 2000]. In preliminary results, Molotch et al. [2001] showed that SWE can begin to vary significantly 500 m beyond from a SNOTEL site, due to terrain impacts on snow
ablation, as well as small scale depositional variations. Snowcourse and airborne gamma SWE data should be introduced into the interpolation.

SNOTEL stations are located in regions for which snow occurs (i.e. mountainous terrain) as shown in Figure 1. In the Colorado River Basin stations located 500 km apart or less may experience similar climatic condition. Serreze et al. [1999] broke the SNOTEL data in the greater basin area into 4 climatic regions based roughly on state boundaries. Therefore, the variation in SWE volume with elevation (Figure 6a-d) is only seen at the lowest and highest elevations, where snow volumes are small. The small increases in volume, as the search radius expands, is due to the incorporation of additional stations with some snow at low elevations, decreasing the regression slope, but increasing the y-intercept. In future, subsets of the data or a search radius will be used with the multi-variate approach. The search radius would be at least 400 km since a minimum number of stations (number of variables in the regression plus one) are required to develop a multi-variate relation. This relates to the distribution of the data and that some remote location, including parts of the Mogollan Rim in Arizona, the Sangre de Cristo Mountains in south-central Colorado, and areas of central Wyoming (Figure 1), are represented by few SNOTEL stations.

A possible directional component in SWE variation anisotropy was based on the assumption is that there is a greater variation in SWE with latitude than with longitude, i.e., the dominant anisotropy approach was that of an ellipse with the major axis oriented east/west and the minor axis oriented north/south. The measurable anisotropy may be due to the differing geographical orientation of the mountain ranges. In the Colorado Basin the majority of the snow lies in the mountain ranges that are oriented north-south,
specifically the Continental Divide and the Wyoming/Wasatch Range and into the northwestern Colorado Plateau. However, snow is also located in mountain ranges that are oriented east-west, such as the Mogollan Rim in Arizona and the Uinta Mountains in Utah. Anisotropy may be useful at a local scale but not on a large basin scale.

Conclusions

The regression (HYP and MVR) interpolation techniques are superior to the distance weighted approaches (IDW and ODA) for interpolated SNOTEL data. The multi-variate regression method had a smaller root mean square error than the other techniques, and the SWE volumes for the entire Colorado Basin were similar to those estimated using the hypsometric approach. However, SWE volumes for the southerly Salt-Verde Basin were overestimated using the multi-variate techniques (MVR and MVR+IDW) as compared to the hypsometric approaches (HYP and HYP+IDW). The regression detrended-inverse weighted distance approaches (HYP+IDW and MVR+IDW) preserve the station values. The elevation detrended-inverse weighted distance approach (HYP+IDW) with a moving search radius, instead of a single regression equation (HYP all data), should be used to develop SWE maps.

There are small differences for the hypsometric method in RMSE and SWE volumes for various search radii and anisotropies of the search ellipse. The RMS error increases as the search radius increases as more heterogeneous station data are included; a search radius of 200 km should be used. Additional results from the MVR+IDW technique need to be generated, including the use of a moving search radius or the distinction of sub-basins for computation, and the use of multiple linear regressions.
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List of Tables

Table 1. Summary of regression parameters, their source, and relative importance of each parameter in the regressions. Notes: ‡ the standard USGS Albers projection was used to identify the relative latitude and longitude; * the distance to the ocean, barrier height, barrier distance, and shield height were measured from the west, northwest and southwest.

Table 2. Average yearly RMSE and bias for the different interpolation methods.
Table 1. Summary of regression parameters, their source, and relative importance of each parameter in the regressions. Notes: ‡ the standard USGS Albers projection was used to identify the relative latitude and longitude; * the distance to the ocean, barrier height, barrier distance, and shield height were measured from the west, northwest and southwest.

<table>
<thead>
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Table 2. Average yearly RMSE and bias for the different interpolation methods.

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Figure 3.
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Figure 9.
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Figure 11.
APPENDIX B: A COMPARISON OF SNOW TELEMETRY (SNOTEL) AND SNOWCOURSE MEASUREMENTS IN THE COLORADO RIVER BASIN
A comparison of snow telemetry (SNOTEL) and snowcourse measurements in the Colorado River Basin

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Abstract

Temporal and spatial differences in snow-water equivalent (SWE) at 240 snow telemetry (SNOTEL) and 500 snowcourse sites and a subset of 93 co-located sites were evaluated by examining the correlation of site values over the snow season, interpolating point measurements to basin volumes using hypsometry and a maximum snow extent mask, and by variogram analysis. The lowest correlation at a point \( r = 0.79 \) and largest interpolated volume differences (as much as 150 mm of SWE over the Gunnison basin) occurred during wet years (e.g. 1993). Interpolated SWE values based on SNOTEL versus snowcourse were not consistently higher or lower relative to each other. Interpolation RMSE was comparable for both data sets, increasing later in the snow season. Snowcourses correlate over larger distances and have less short-scale variability than do SNOTEL sites, making them more regionally representative. Using both data sets in hydrologic models will provide a range of predicted streamflow, which is potentially useful for water resources management.

KEYWORDS: snow water equivalent, SNOTEL, snowcourse, Colorado River
1. Introduction

Much of the streamflow in the Colorado River and other rivers in the southwestern United States is derived from seasonal melt of mountain snowpack (Serreze et al., 1999). Estimates of water stored as snow, i.e. snow water equivalent (SWE), are essential for forecasting runoff, understanding climate change (McGinnis, 1997), carrying out forest management, and many other applications – yet making accurate basin-scale measurements has remained an unmet challenge for decades (Johnson and Schaefer, 2002). In the western U.S. SWE has been measured at key index sites, or snowcourses, since the 1930’s. Empirical forecasts of seasonal streamflow volume were historically based on at least 20 years of data, regressing snowcourse, precipitation, soil moisture and observed streamflow. In 1963 the United States Department of Agriculture (USDA) Soil Conservation Service began the installation of an automated network of snow telemetry (SNOTEL) sites, which are now operated by the USDA National Resource Conservation Service (NRCS). The system replaced some manual snowcourses and provides continuous real-time SWE data for seasonal streamflow volume forecasting (Johnson and Schaefer, 2002). SNOTEL sites were placed at or near snowcourses that exhibited high correlations with streamflow (Schaefer and Johnson, 1992), locations exhibiting uniform snowcover and thought to represent snowpack conditions specific to the elevation and aspect of that particular sub-basin (Palmer, 1986).

While SNOTEL and snowcourse networks were developed as predictors for seasonal runoff, these estimates typically have errors, especially when conditions are far from the mean. One promising approach to improving the accuracy of seasonal forecasts is to use estimates of spatial SWE and snow covered area (SCA) in more physically based
hydrologic models (e.g. Leavesley et al., 2002). These approaches provide snowmelt runoff timing and spatial depletion patterns as well as seasonal volumes. It should be noted, however, that snowcourse networks were not designed as measures of the absolute amount of SWE in a basin – let alone yield SWE estimates across a basin. However, for the present, these are the best data available on historical SWE across the western U.S.

This paper examines spatial differences in basin-wide SWE estimated using SNOTEL vs. snowcourse data for the Colorado River basin. We first compare differences in point values at co-located SNOTEL and snowcourse stations over representative dry, average and wet years. To evaluate differences between the datasets in estimating total water resources from snow, basin-scale SWE was estimated using hypsometric interpolation of point SNOTEL vs. snowcourse measurements, and combinations of the two data sets. Knowledge of spatial differences between SNOTEL and snowcourse data at the point and basin scale will better inform applications such as water resource management regarding issues of using either data source for operations or modeling.

2. Study Area

The Colorado River basin (Figure 1) is over 1,300 km long and up to 800 km wide. Most of the basin’s snow is found in the Upper Colorado basin, which has a drainage area of 277,000 km², an elevation range of 975-4,260 m and an average elevation of 2,150 m. The Lower Colorado has a drainage area of 346,000 km², with an elevation range of 0-3,771 m and an average elevation of 1,310 m. Almost 60% of the Upper Colorado, but only 16% of the Lower, is above 2,000 m. The snow in the Lower Colorado is located
along the Mogollan Rim in east-central Arizona, up through the Colorado Plateau
approaching the Grand Canyon, and in western New Mexico. The focus of this paper is
the entire Colorado River (623,000 km²) and three sub-basins: Gunnison (20,500 km²),
San Juan (63,700 km²), and Salt-Verde (35,100 km²) (Figure 1). These basins were
chosen to represent large portions of snow for the Upper Colorado (Gunnison and San
Juan) and the Lower Colorado (Salt-Verde) and to represent a range of terrain complexity
and forest density.

3. Data and Methods

Snow telemetry (SNOTEL) SWE data are available for more than 600 sites and
snowcourse data for nearly 2,000 sites in the western U.S. from the NRCS
(http://www.nrcs.usda.gov). Snowcourses provide snapshots of SWE near the 1st of each
month, based on the average of 10 manual measurements at each site. SWE is measured
by inserting a hollow aluminum or steel tube into the snow, extracting a core and
weighing it. Some manual snowcourses have been eliminated as more automated stations
have been established and their use in water forecasts accepted. At the SNOTEL sites,
snow accumulating over a fluid-filled pillow forces the fluid into a manometric column
and height changes are recorded.

This study examines SWE measurements within and adjacent to the Colorado River
basin using 240 SNOTEL and 500 snowcourse stations, 93 of which are co-locations
(Figure 1). The 1990-1999 period was examined due to an increase in the number of
SNOTEL stations reporting after 1990 and as a complement to the earlier study of
Serreze et al. (1999), which compared co-located SWE values for 1980-1987 within the
same domain on April 1, a date generally corresponding to peak SWE. Within the 1990-1999 period three years are analyzed in more detail, those representing above average, near average, and below average accumulation years. While there were differences across the basin, 1993 was typically an above average year, whereas 1998 and 1999 were near and below average, respectively. March 30 was chosen as the comparison date to both approximate peak SWE and to coincide with the date of the maximum number of stations recording snow.

Comparing the elevational distribution of the 240 SNOTEL and 500 snowcourse sites with that for the snow-covered part of the Colorado River basin, it is apparent that SNOTEL sites are clustered more at lower to mid elevations and snowcourses are more representative of basin as a whole (Figure 2). Snowcourses, however, under-sample elevations > 3,500 m (only 16% of the area in the upper Colorado, but contains a lot of the snow).

Data quality control procedures followed those developed by Serreze et al. (1999) for SNOTEL data, which masked outliers and eliminated negative SWE values. Stations with missing values for the first 15 days of the water year were assumed to have had delayed servicing; data for that year were not used. Daily SWE increments greater than 25 cm, or consecutive days with increases and subsequent decreases each greater than 6 cm, were deemed erroneous and unused. Monthly SWE decreases more than five standard deviations from the mean were deemed to be erroneous, and monthly SWE increases more than five standard deviations from the mean without a comparable extreme value for precipitation or a corresponding precipitation increment of more than three standard deviations were deemed to be erroneous. When erroneous data were
identified at a site subsequent SWE measurements for that water year were not used, in order to eliminate the contaminating effect of an individual erroneous value.

Point values were interpolated using hypsometry (SWE regressed with elevation) and elevation detrended residuals, as done in Fassnacht et al. (2003). Five data combinations were used: i) SNOTEL only, ii) snowcourse only, iii) co-located SNOTEL plus snowcourse for measurement days only (mmt), iv) co-located SNOTEL plus snowcourse for all days, with linear interpolation of snowcourse values between measurement days (linear fill), and v) co-located SNOTEL plus snowcourse for a 2-day linear interpolation around the measurement day (partial fill) – data not shown as it added no insight beyond the other two combinations. The number of snowcourse sites (from linear interpolation) reporting exceeded the number of SNOTEL observations during peak snow accumulation (Figure 3).

4. Results

The largest differences in yearly average SNOTEL and snowcourse values were in 1993, the year with the most snow, and the only year in which average snowcourse SWE exceeded that for co-located SNOTEL sites (Table 1). The average Pearson’s correlation coefficient for SWE at co-located sites ranged from 0.79 in 1993 to 0.96 in 1996. While the correlation was lowest in 1993, the difference between the means (-5 mm) was small; however, using means masks extreme site-specific differences that occur when SWE values are medium to high (Figure 4). Water years 1998 and 1999 exhibited small differences in SWE at co-located sites, except for a few cases with SWE values less than 500 mm.
For the Gunnison, San Juan and Salt-Verde basins, SWE estimated from interpolated SNOTEL data (Figure 5a-c) was consistently higher than for snowcourse data, with greatest differences, as much as 150 mm or 40% over the Gunnison at 3,000-3,500 m elevation, at peak SWE. The RMSE for interpolated SWE (1 km² grid) versus observed point values increased through May and then declined as snow cover became nearly depleted (Figure 6). Average interpolated SWE for the Colorado basin as a whole was greater when using snowcourse versus SNOTEL data, with the largest difference at lower elevation (1,500-2,000 m) (Figure 7).

Snowcourse variance was best modeled by the Gaussian model (Figure 8), while SNOTEL was best modeled by the spherical model, as determined by maximizing the “indicativeness of fit” parameter, a statistical measure of model fit to data variance across spatial lag distances, in the UNIX-based GEOEAS software. Variogram model fits for 1993 show that snowcourse data had an approximate range (correlation length scale, defined as the range, or the practical lag distance at which covariance does not change significantly with increasing lag distance) of 500 km for co-located sites and 550 for all snowcourse locations, while SNOTEL data had a correlation length scale of approximately 300 km. Snowcourse correlation length scales in the average snow year of 1998 (400 km) were smaller than in 1993, but within the dry snow year of 1999 (500 km), they are comparable (Table 2). In all cases the nugget, defined as the discontinuity at the origin of the variogram, explained by factors such as sampling error and short-scale variability (Issaks and Srivastava, 1989), was larger for SNOTEL than for snowcourse data and as much as twice that of co-located snowcourse data for 1993 and 1999. Nugget
values are largest in 1993 and smallest in 1999 for both data sets, and larger for SNOTEL than snowcourse for all years.

5. Discussion

The 1990-99 average correlation (0.90) for the 93 co-located sites is the same as Serreze et al. (1999), in which they calculated correlation for the 1980-1987 period using 92 of the same co-located sites. Higher correlations generally occurred during years of lower snow accumulation. However, relative differences in season-average SWE were somewhat smaller in higher-accumulation years, e.g. 1% in 1993 versus 13% in 1999. The four years with the greatest relative differences (9-13%) had a mean peak SWE of 191 mm versus 232 mm for the six years with the lowest relative differences (1-5%). This may simply reflect greater local-scale variability in drier years.

Though SNOTEL sites are susceptible to various sensor inaccuracies (Peck, 1972; Smith and Boyne, 1981; Johnson and Schaefer, 2002; Johnson, 2004), this was not likely to be a major factor in the observed differences, as correlations in both this and past studies (Serreze et al., 1999) were relatively high. SNOTEL sites measure daily changes in SWE, but inaccurate measurements can be made due to instrumentation sensitivities and equipment issues such as ice bridging across the snow pillow (Goodison et al, 1981). Snowcourses cover a larger area than do SNOTEL measurements, making the former more susceptible to environmental factors such as snow drifting, wind scour or falling debris. Though both are located on relatively flat ground, minor differences in aspect, exposure and vegetative cover may also affect patterns and produce different melt rates during the ablation period (Palmer, 1986).
The largest differences in interpolated SWE estimated from SNOTEL versus snowcourse data in the three sub-basins (Figure 5) occurred at 2,500 –3,500 m, the elevation range with the most observations (Figure 2) and the greatest amount of snow. However, in the Colorado basin as a whole, the interpolated SWE estimates differed most at 1,500-2,000 m (Figure 7), an elevation range with few SNOTEL sites (Figure 2). The conflicting SWE volume differences are caused by two factors. First, the elevational distribution of snowcourse and SNOTEL stations reporting differs, resulting in different representations of each elevation in the interpolation. Second, there are differences in point SNOTEL versus snowcourse data, as noted above.

The number of stations reporting increased until March and then decreased through May as the snow melted. The different data combinations showed similar differences in RMSE over the snow season, except during the first and last measurements at the snowcourses. Higher snowcourse RMSE for these dates was due to the small number of snowcourse stations reporting (Figure 4a). Interpolated snowcourse SWE values were greater than those for SNOTEL at all elevations for the Colorado River basin as a whole (~10⁵ km²), but less than SNOTEL values in the sub-basins (~10⁴ km²), indicating that selection of SWE data for particular applications may need to be spatial scale specific. It also implies that other regions of the Colorado basin have measurement biases between the data sources, differing from those sub-basins studied here.

Variogram analysis was used to evaluate differences in the spatial correlation between SNOTEL and snowcourse data and to determine why interpolated estimates were different. Snowcourse data were correlated over a larger spatial scale than SNOTEL. This implies an interpolation model using SNOTEL data should employ a
smaller search radius, up to 300-km, while a model using snowcourse data could use a search radius up to 500-km (Table 2). Nugget values were larger overall during wet (1993) versus dry (1999) years and were greater for SNOTEL than snowcourse for all study years, indicating larger short-scale variability or measurement error within the SNOTEL data set and during periods of above average and below average snow. A Gaussian model, known as a model that approximates continuous phenomenon, was the best fit for snowcourse versus a spherical model for SNOTEL. This reflects the spatial pattern of the snowcourse as well as the greater number of sites than SNOTEL.

6. Conclusions

While SNOTEL were implemented to replace the snowcourses, measurements at co-located sites indicate generally small differences in SWE at the point scale, but these differences translate to large interpolated volume differences at the basin scale. Accuracy is of most concern in wet years such as 1993, in which greatest absolute differences in SWE at co-located sites occur, but large relative differences in dry years could also be a problem when data are used to inform water resources decisions. Interpolation to estimate regional SWE produces greater differences in basin-wide water volumes (e.g. 50 mm of SWE over the entire Gunnison basin in 1993 at 3250 m elevation, alone), depending on which data or combination of SWE data are considered; however, both data sets produced comparable interpolation errors.

Variogram analysis indicates that snowcourse measurements have less short-scale variability and possibly less measurement error along with a longer correlation length scale. It is not clear from this analysis which data set is more accurate for use in applications such as water-supply forecasting. However, for basin-wide SWE estimates
snowcourse data are more representative of the elevational distribution in the basin.

Consideration of both data sets and combinations of the two are good for characterizing high and low estimates of peak basin-wide SWE, especially for hydrologic modeling on spatial scales of the Colorado basin (10⁴-10⁵ km²), for which small differences in point estimates translate to large errors in area estimates from interpolation. The range of SWE values from the different data sets and their combinations is valuable in the context of water supply forecasting in that an interpolated SWE surface based on one particular data set does not indicate any measure of accuracy, especially since the current network was not designed for the purpose of calculating basin-average SWE.

Although the range of SWE values generated by the two data sources is valuable, it is difficult to ignore the utility in the automatic, daily sampling of SNOTEL. Snowcourse are infrequent (once or twice a month) and dependent on weather conditions in many cases, but they are more representative of basin elevation (a strong influence on SWE). This trade-off in usability must be considered in modeling, as the impact of assimilating snow information for water supply forecasting is increased with higher frequency observations in locations representative of elevation and associated SWE amount.
Acknowledgements

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Table 1. Co-located snowcourse and SNOTEL SWE on March 30.

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Table 1. Co-located snowcourse and SNOTEL SWE on March 30.

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Table 2. March 30 variograms for snowcourse and SNOTEL data.

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Figure 1. Location map.

Figure 2. Cumulative frequency of recording SNOTEL and snowcourse station elevation locations relative to Colorado basin topography and as masked by the snow-covered portion of the basin.

Figure 3. 1993 weekly SNOTEL and snowcourse stations reporting (after quality control), as used for hypsometric interpolation. The number of snowcourse on this graphic was calculated from a linear interpolation between snowcourse measurement days (linear fill). Additional mixed data sets (data not shown) included SNOTEL plus co-located snowcourse on measurement day only (mmt) and SNOTEL plus snowcourse for all days, with linear interpolation of snowcourse values between measurement days (linear fill).

Figure 4. Measured SWE for SNOTEL versus co-located snowcourse along the 1:1 line for above average (a) 1993, average (b) 1998, and below average (c) 1999 snow years.

Figure 5. March 30, 1993 hypsometrically interpolated SWE (normalized by basin area) using various combinations of data, by sub-basin. Refer to figure 3 for data set combinations.

Figure 6. March 30, 1993 RMSE interpolation error, calculated from the difference of the 1-km² gridded values and the point data used to compute the gridded values within the Colorado Basin. Refer to figure 3 for data set combinations.

Figure 7. March 30, 1993 elevational dependence of interpolated SWE volume differences for co-located sites over the Colorado River basin. Interpolations are masked
by maximum snow extent from AVHRR SCA. Refer to figure 3 for data set combinations.

**Figure 8.** March 30, 1993 variograms and model fits for the Colorado River basin.
Figure 1. Location map.
Figure 2. Cumulative frequency of recording SNOTEL and snowcourse station elevation locations relative to Colorado basin topography and as masked by the snow-covered portion of the basin.
Figure 3. 1993 weekly SNOTEL and snowcourse stations reporting (after quality control), as used for hypsometric interpolation. The number of snowcourse on this graphic was calculated from a linear interpolation between snowcourse measurement days (linear fill). Additional mixed data sets (data not shown) included SNOTEL plus co-located snowcourse on measurement day only (mmt) and SNOTEL plus snowcourse for all days, with linear interpolation of snowcourse values between measurement days (linear fill).
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APPENDIX C: EVALUATION OF GRIDDED SNOW WATER EQUIVALENT AND SATELLITE SNOW COVER PRODUCTS FOR MOUNTAIN BASINS IN A HYDROLOGIC MODEL
Evaluation of gridded snow water equivalent and satellite snow cover products for mountain basins in a hydrologic model

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Abstract

The USGS Precipitation Runoff Modeling System (PRMS) hydrologic model was used to evaluate experimental, gridded, 1-km² snow covered area (SCA) and snow water equivalent (SWE) products for two headwater basins in the Rio Grande and Salt River drainages in the Southwestern United States, developed by the Southwest Regional Earth Science Applications Center (RESAC). The SCA product was the fraction of each 1-km² pixel covered by snow and was derived from NOAA Advanced Very High Resolution Radiometer imagery. The SWE product was developed by multiplying the SCA product by SWE estimates interpolated from National Resources Conservation Service Snow Telemetry (SNOTEL) point measurements for a six-year period (1995-2000). Measured SCA and SWE estimates consistently underestimated modeled SCA and SWE estimated from temperature and precipitation. Differences between modeled and measured snow were different for the accumulation period vs. the ablation period and had an elevational signature. Greatest difference occurred in the relatively complex terrain of the Grande as opposed to the Black. Because the RESAC snow fields are systematically lower than model fields, assimilating them into a version of PRMS previously calibrated to achieve an adequate water balance reduced model performance by removing water in both basins, with the negative impact accumulated through the season. Hydrologic models incorporating RESAC SCA and SWE must be recalibrated to adjust to measured inputs.

KEYWORDS: assimilation, snow water equivalent, snow covered area, hydrologic modeling, PRMS
1. Introduction

Accurate snowpack and snowmelt estimates in cold regions are critical for operational flood control, water delay planning, and resource management in snowmelt-dominated basins. Snow-covered area (SCA) has been used as a driving hydrologic variable for streamflow prediction (e.g., Martinec, 1975; Rango and Martinec, 1979; Barrett et al., 2001). Observations of areal extent have been used in hydrologic model forecasts for decades (Maurer et al., 2003), and many studies have focused on using SCA to estimate snow water equivalent (SWE) through depletion curves (e.g., Anderson, 1973; Liston, 1999). Ground estimates of SWE are essential for physically based snowmelt runoff models, which include mass balance of water (Molotch et al., 2004a) and have been used for evaluation of energy-balance snow models (e.g. Cline et al., 1998). However, estimating snow cover properties at a basin scale, particularly SWE but also SCA, remains a challenge.

Hydrologic models generally involve time-invariant descriptions of basin characteristics through parameters (e.g., temperature-precipitation relationships) and variable states (e.g., flux, storage and residence time of snow) (Moradkhani et al., 2005). These models require accurate initial conditions to adequately simulate runoff (Day, 1985). Accurate snowmelt runoff estimation in hydrologic models is a challenge, especially in mountainous terrain where the signature of snow is large (Fontaine et al., 2002) and data are poor in spatial resolution (Davis and Marks, 1980). Cazorzi and Fontana (1996) improved data resolution by distributing temperature, a primary forcing variable in snowmelt (Zuzel and Cox, 1975), with distributed solar radiation and adiabatic lapse rate. Both energy budget (e.g., Anderson, 1976) and temperature-index or
degree-day (e.g., Martinec et al., 1983) snowmelt models are routinely used in hydrologic models. Temperature-index models are widely used because the data needed for energy budget approaches (Rango and Martinec, 1995; Cazorzi and Fontana, 1996; Walter et al., 2004) is often unavailable.

Operational forecasts of streamflow could benefit from updated estimates of distributed snow cover. Satellite remote sensing in the visible and near-infrared wavelengths has been used operationally for many years to map snow cover (e.g. Cline et al, 1999), however there has been little evaluation of the impact of assimilating those spatial snow products in mass and energy balance hydrologic models for streamflow estimation over a large spatial scale. The United States Geological Survey’s (USGS’s) precipitation-runoff modeling system (PRMS) is well-suited for such evaluation. PRMS is a modular, deterministic, distributed-parameter modeling system developed to evaluate the impacts of various combinations of precipitation, climate, and land use on streamflow, sediment yields, and general basin hydrology (Leavesley and Stannard, 1995). PRMS has performed well in simulating streamflow in mountain basins, e.g. the Upper Gunnison River, CO (Leavesley et al., 2002). In that study, remotely sensed estimates of binary SCA from the US National Weather Service National Operational Hydrologic Remote Sensing Center (NOHRSC, http://www.nohrsc.nws.gov) were similar to SCA simulated by PRMS over the period 1990-1999. This reasonable agreement independently validated the viability of the PRMS parameter estimation approach in mountainous terrain. Many techniques have evolved for updating models, including simple “replacement” or “updating” of state variables to more complex four dimensional data assimilation used in meteorological applications (Stauffer and Seaman,
1990), and the potential model improvements depend on both the quality of the input data and accurate parameter estimation (Moradkhani et al., 2005).

This study is a comparative evaluation between the RESAC SCA and SWE products (with and without a vegetation correction) and a modeled snowpack (estimated from temperature and precipitation) in two headwater basins. We used PRMS (Leavesley et al., 1983) due to its minimal forcing data requirements and previous success in simulating snow packs in the study region. Differences between modeled and measured fields are evaluated in time and space and in the context of simulated discharge from those different fields.

2. Data and Methods

Study Area

The Black River headwaters of the Salt River near Phoenix, AZ is a 1441 km$^2$ basin with elevation ranging from 3334 m in the northeastern section of the basin to 1761 m at the stream gauge (USGS 09489500 near Point of Pines, AZ; operating since 1953), an average elevation of 2454 m (Figure 1). The Rio Grande headwaters, above the Del Norte, CO stream gauge, is a 3397 km$^2$ basin with elevation ranging from 2438 m at the gauge (USGS 0822000; operating since 1890) to 4084 m in the northwestern alpine portion of the basin, and an average of 3225 m (Figure 1). Both basins are heavily forested and precipitation is dominated by snow, but the Grande is higher elevation and more topographically complex than the Black. Average stream flows are 24.1 m$^3$/s and 5.8 m$^3$/s, respectively.

Serreze et al. (1999) report that the western United States can be divided into 8 regions that are topographically, climatologically, physically, and hydrologically
different. Although within region differences are expected on the smaller scale, regional
heterogeneities are expected to dampen that signature. The Grande and Black basins are
located in different regions (Black, Arizona/New Mexico region; Grande, Colorado
region), and therefore, enable evaluation of differences in satellite-based SCA, SWE, and
runoff estimation over differing basin characteristics found in southwestern mountains.

Snow Data

SCA maps for the Grande and Colorado River basins of the Southwestern U.S.
were developed for a six year period (1995-2000) from AVHRR scenes using a three-part
cloud masking procedure spectral un-mixing algorithm (Bales et al, in preparation).
Level 1b AVHRR scenes were acquired through the University of California-Santa
Barbara and New Mexico State University. Processing occurred in three steps. First,
images were converted from digital counts to radiances for all 5 bands, then to surface
reflectance for bands 1 (0.58-0.68 µm), 2 (0.725-1.10 µm), and 3 (3.55-3.93 µm), and to
brightness temperature for bands 3 (3.55-3.93 µm), 4 (10.3-11.3 µm), and 5 (11.5-12.5
µm). Atmospheric corrections were made on the reflectance bands (1-3). These 3 bands
were then introduced into a decision-tree algorithm, which is based on training against a
set of 532 cases of mixtures of 23 theoretical spectra of snow, vegetation, and snow types
(Rosenthal and Dozier, 1996). The decision-tree algorithm returns fractional SCA for
each pixel likely to be covered by snow, in 16 discrete increments: 0.0, 0.1, 0.18, 0.21,
0.3, 0.32, 0.38, 0.45, 0.47, 0.56, 0.58, 0.66, 0.74, 0.82, 0.89, and 0.99. The result is a
mixed product of snow, clouds, and highly reflective surfaces, which must be corrected to
give just the snow-covered pixels. Secondly, a supervised cloud mask was constructed.
An additional aperiodic “no data” mask was generated to account for pixels within the
study area, but outside the AVHRR swath during overpass. Thirdly, a temperature mask was generated to eliminate highly reflective surface features that are unlikely to be snow. Many highly reflective surfaces (light colored desert sand, dry lake beds, water) are warmer than snow. Pixels were identified using a supervised classification of brightness temperatures for band 4.

Fractional SCA in each pixel was estimated, scenes georegistered, orthorectified, and gridded to 1-km\(^2\). Since some clouds were present in most scenes, all scenes with at least one major headwater basin (e.g. Grande) cloud free were processed. In doing so, 229 days were processed for January 1 – June 30 during the 1995 – 2000 period (Table 1). This fractional SCA product was developed by the Southwest Regional Earth Science Applications Center (Southwest RESAC) at the University of Arizona in Tucson, Arizona.

Spatially distributed SWE was estimated daily at a 1-km\(^2\) resolution for the same area by interpolating point SWE measurements from SNOTEL stations (Fassnacht et al., 2003) operated by the National Resource Conservation Service (NRCS) (http://www.nrcs.usda.gov). For each grid cell in the basin, all SNOTEL sites within a 200-km radius, including those outside of the basin, were identified. A linear regression was computed between elevation and SWE for all of the SNOTEL sites within the search radius. This hypsometric relationship was used to estimate SWE for each grid cell using a 1-km digital elevation model (DEM). A residual was obtained at each grid block where an observing SNOTEL station was located by removing the observed value from the analysis, i.e., jack-knifing, and subtracting the observed SWE from the computed SWE. Elevation dependent bias in the residuals was removed by regressing residuals to a datum
of 5,000 meters above sea level using the dry adiabatic lapse rate. Once regressed to the common datum, the lapsed residuals were spatially distributed using inverse distance weighting with a power of 2. The gridded residual surface was regressed back to the basin surface using the same lapse rate and subtracted from the hypsometrically derived SWE grid in order to derive the final SWE surface. Daly et al. (2000) used a similar method, except one hypsometric relationship was computed for each sub-basin, instead of using a moving search radius to compute the hypsometric relationship at each pixel. Total basin SWE was then obtained by multiplying the interpolated SWE product with the fractional SCA product. In this way the interpolated SWE maps were adjusted on a pixel-by-pixel basis for the fraction of area determined as snow covered.

RESAC SCA and SWE were adjusted by applying a pixel-by-pixel canopy correction for all 229 product days. First, a day with maximum change in SWE from the previous few days and minimum clouds was selected for each basin. March 3, 1996 was selected for the Grande, for which a basin average of 104 mm of snow fell 9 days before; and March 2, 1997 was selected for the Black, for which a basin average of 213 mm of snow fell the day before. It was assumed that if > 75 mm of snow fell and daily maximum temperatures after that precipitation did not exceed 0°C, the ground should be snow covered and therefore a value of 99% SCA, the highest classification value for the RESAC SCA product. Second, pixels that contain any forest (from the gridded 1-km USFS vegetation type data set; USDA, 1992) and are above 2100 meters elevation (considered as the maximum snow extent for the dataset) were identified for correction. All other pixels and those mapped as clouds were assigned a canopy factor of 1, i.e. no correction. Third, the pixel-by-pixel canopy factor was calculated by dividing 99%
(maximum AVHRR SCA) by the mapped value in the pixel to get the pixel-specific canopy correction factor (Figure 2). Fourth, total SWE in each pixel on all remaining 229 days snow was multiplied by the pixel canopy correction factor.

**Hydrologic Model**

Catchment characteristics used in the model were defined using ArcInfo (ESRI, 1992) ARC macro language (AML) functions with digital databases to calculate distributed model parameters (e.g., elevation, slope, aspect, available water holding capacity of the soil, stream reach slope, vegetation cover density). Digital databases used for this study include: (1) USGS 30 m digital elevation model; (2) State Soils Geographic (STATSGO) 1-km gridded soils data (USDA, 1994); and (3) US Forest Service 1-km gridded vegetation type and canopy density data (USDA, 1992). PRMS hydrologic response units (HRUs) were defined as the same 1-km² grid as the AVHRR data. That is, each AVHRR 1-km SCA cell is an HRU.

An objective calibration procedure similar to the one in Leavesley et al. (2002) for other western USA basins was used. No changes were made to spatial parameters, and the calibration focused on water balance parameters affecting potential evapotranspiration (ET) and precipitation distribution and on the subsurface and groundwater parameters affecting streamflow volume and timing. Simulated potential ET was adjusted manually to match published values for the region and gauge catch corrections for snow were applied manually to minimize the difference between simulated and observed streamflow. This base parameter set was used for all model runs in order to maintain a base condition for comparison purposes. Adjusting parameters
differently in each model run would bias simulations to particular snowpack characteristics associated with each input dataset.

PRMS requires distributed estimates of temperature and precipitation as forcing variables. We used the xyz approach (Hay et al., 2000; Hay and McCabe, 2002; Hay et al., 2002) to distribute National Weather Service (NWS) cooperative climate observing station point values of precipitation, and maximum and minimum daily temperatures across the HRUs. Four climate stations were selected for the Black and twelve were selected for the Grande. Data at sites included in a 50-km buffer surrounding the study basins were extracted from the National Climatic Data Center (NCDC, 2004) Summary of the Day (TD3200) summarized by Eischeid et al. (2000) and obtained online at <http://www.ncdc.noaa.gov/oa/climateresearch.html>. Quality-control procedures of Reek et al. (1992) were applied. Records at most stations start in 1948 and continue through present.

**Assimilation Approach**

We used the simple replacement or update technique of Jastrow and Halem (1970), i.e. measured, gridded SCA and SWE replaced PRMS model SCA and SWE in each HRU at each time step data are available. This technique was used, as opposed to a more complex averaging or nudging technique, for the purpose of evaluating the measured SCA and SWE against a simulated estimate from temperature and precipitation data. If no data were available in any given pixel (i.e. cloud), the model values were carried forward to the next time step. We compared spatial SCA and SWE for remotely-derived products and a base model case to evaluate the spatial distribution of RESAC
estimates. Discharge was then compared for five simulations using model updates from satellite-derived SCA and SWE and a model base case.

Simulation runs were:

- “base” – PRMS model with no data assimilation
- “remote” – model updated with both SCA and SWE
- “remote SWE” – PRMS model using an update from SWE data, with SCA simulated within the model and not updated
- “filtered” – PRMS model updated with both SCA and SWE smoothed with a 9-km$^2$ low-pass averaging filter
- “veg correct” – updated from the canopy corrected SCA and SWE estimates.

These simulations were repeated for the Grande using measurement updates only through April 1 each year (peak SWE), for a total of 116 updates. These simulations with the April 1 cutoff date initialized the model snowpack state for the snowmelt period and were compared to simulations that update during the ablation period to evaluate potential water losses from updates of measured snow fields.

For pixel updates from remote sensing of SWE > 0, the internal dynamics of the snowpack were maintained consistent with the pre-existing pack by adjusting snowpack physical states of free water holding capacity, cold content, and depth. Energy balance equations may be referenced in Leavesley and Stannard (1995). The snow depletion curve was updated with SCA estimates, when available, and reset for every pixel in the basin, adjusting the threshold magnitude to maintain a consistent SCA/SWE relationship with the predefined depletion curve from Anderson (1973).
3. Results

Measured SCA and SWE were systematically lower than modeled SCA and SWE in the Black (Figure 3) and Grande (Figure 4) basins over the 1995-2000 period. Underestimation was generally greater for the Grande than for the Black for both SCA and SWE. In Figures 3 and 4, the representative average water year (WY) 1998 is shown to further illustrate the differences. Total SWE followed the pattern of SCA. However, in some cases for the Black, total measured SWE was greater than modeled SWE, while measured SCA was less than modeled SCA for the same day (e.g. February 10, 1998). This is an artifact of the ground-based SWE data. The vegetation correction decreased the difference by adding snow in forested areas. The average canopy factors of 3.3 for the Black and 2.3 for the Grande, however, did not increase SCA and SWE everywhere due to the presence of clouds for which no correction was applied.

Differences between modeled and measured SCA were dependent on elevation (Figure 5). On average, SCA and SWE were always higher for the model. During the accumulation period, differences generally decreased with elevation for both basins. The elevational trend in the ablation period differed from the accumulation period: it increased to a peak in the 3000-3500 m elevation range and then decreased above 3500 m. The greatest differences occurred in the Grande, with a maximum of 67% in the 3000 – 3250 m region. The canopy correction improved upon the satellite estimate at all elevations, with the greatest impact at mid-elevations (2750 – 3500 m) where most forest and complex terrain occurs. Differences in SWE followed the same general trends as differences in SCA for both basins (Figure 6), but with less variability. However, measured SWE was greater than modeled during the accumulation period for the Black.
Replacement of modeled SCA and SWE with measured updates reduced model performance as shown in the water balance (Table 2) and cumulative discharge (Figure 7). Overall low Nash-Sutcliffe values in the Black were due to inaccuracies in estimating both runoff volume (over and underestimates) and timing (earlier melt), common problems in semi-arid basins for which streamflow is low (Figure 7). Black basin simulations with updates generally over-predicted streamflow during wetter years (WY 1995 WY 1997, and WY 1998) due to the higher SWE estimates after interpolation, and under-predicted during drier years (WY 1999 and WY 2000) due to less consistent snowpack coverage, i.e. patchier snow, which can lead to a mixed snow and terrain signature. Grande simulations with updates systematically under-predicted relative to both the base simulation and observed cumulative discharge in all years.

In the Black, the updated simulations overestimated the modeled and observed discharge during the rising limb of the hydrograph due to the positive change in SWE volume when replacing model snow fields with measured snow fields (Figure 8). After March 1, the measured updates removed SWE when replacing modeled fields. This decreases the discharge for both updates simulations. In all update cases for the Grande, model performance was reduced as measured snow fields removed SWE from the basin (Figure 8). The negative impact progressively increased through peak discharge and melt-out to base flow conditions, because, as discussed earlier, the measured fields were systematically lower than modeled (Figure 4). During WY 1998 in the Grande basin, the response to April snow events was lagged in the hydrograph with the remote case melting out earlier and a lower peak magnitude due to the replacement of modeled fields with lower measured SCA in the four May updates, an average of 73% less SCA. Because
snow is updated after the accumulation period, the lower estimates in the update removed snow that is not redistributed or added at a later date. An additional set of model runs were performed for the Grande with updates only through April 1 (Figure 9), as an ablation season initialization of snowpack. Because SWE was not removed during the ablation period by lower measured snow updates (Figure 4), simulated discharge was improved through better water balance and Nash-Sutcliffe values (Table 2).

4. Discussion

Measured SCA and SWE estimates were systematically less than the modeled estimates for both basins (Figures 3 and 4). Highest underestimates were in the Grande due to heterogeneous terrain and ubiquitous forest in the mid-elevation zone (2750 – 3500 m). Remotely based SWE is produced from combining interpolated ground based SWE from SNOTEL and SCA from AVHRR. Therefore, the elevational trend of SWE differences (model – measured estimate) was similar to and heavily influenced by SCA (Figure 6). The canopy corrected SWE gave an improvement (relative to modeled fields) upon the original remotely derived estimate in both basins, reducing the average pixel difference over the dataset by more than 50% for the Grande during the accumulation period.

The lower spatial resolution of AVHRR SCA (1-km²), as compared to the Moderate Resolution Imaging Spectrometer (MODIS) (500-m), potentially introduced more mixed pixel signatures. Mixed pixels were most evident in the complex terrain, which had a more heterogeneous distribution of vegetation, soil and snow, for example. Similar results were reported in Barrett et al. (2001) in which fewer successful matches of modeled and satellite-derived SCA were made in vegetated, heterogeneous terrain of the
East River basin, Colorado. Marsh et al. (1999) reported that both model and satellite estimates of SCA in topographically complex and forested areas were less accurate than in relatively homogeneous, non-forested areas. Additionally, Maurer et al. (2003) compared the SCA product of MODIS with the binary product of the National Operational Hydrologic Remote Sensing Center (NOHRSC). They concluded the higher resolution MODIS (500-m) mis-classified less ground observations of snow than NOHRSC (1-km$^2$) in the more heavily forested complex terrain of the Columbia basin, indicating an improvement in classifying snow in the presence of clouds. Geo-registration errors associated with measured SCA are known to be as much as 2 km in some cases, causing shifts in consecutive scene snowpacks (Bales et al, in preparation). This shift can cause snow distribution errors that influence the discharge timing and magnitude from ablation season melt.

Measured SCA estimates detected less snow than the xyz model method in the topographically complex and forested higher elevations of the Grande (Figure 4), which led to lower runoff estimates and earlier melt-out to base flow in the spring (Figure 8) when replacing model snow fields with measured snow fields. A canopy correction improved the SCA product at elevations above 2500 m in the Grande due to a large signature of forest (e.g. 88% forest in the 3000 – 3250 m elevation range) and to a lesser extent at the highest elevation (3750 m and above), for most of those pixels were above the tree line, and no correction was applied. The average canopy factors of 3.33 for the Black and 2.3 for the Grande do not increase SCA in every pixel due to clouds, which cannot be corrected. For example, all pixels for May 5, 1997 in the Grande and March 26, 1997 in the Black are classified as cloud.
April 1 is the approximate date of peak SWE in the Colorado region over the study period, for which the Grande headwaters is a part (Serreze et al., 1999). When using updates only through April 1 (considered an initialization of ablation period melt), the magnitude and timing of streamflow improved, because less updates remove water from the catchment. The simple replacement technique used in PRMS did not account for mass losses (i.e. measured values of SCA and SWE are lower than the xyz model) in the ablation period, because water losses were incurred through measured updates (i.e. removed water from the basin), but those losses were not distributed among mass and energy states in this study.

The PRMS model requires reliable, distributed estimates of climate variables (daily precipitation and temperature values) at each HRU to drive the model and simulate a snowpack. Many geographic factors (e.g. elevation) affect this distribution. The xyz approach distributes precipitation and temperature first by determining if precipitation occurs (binary decision) in the basin and then interpolates the values using monthly multivariate regressions of the spatial relations between geographic variables (independent) and the climate variables (dependent variables). This monthly relationship may not hold true throughout the month because extreme storm conditions are likely to occur in the Grande during the relatively windy month of March, for example. Remotely sensed snow and ground based SWE can serve as estimates of precipitation inputs and model melt-rate formulations in these cases. To further improve SCA in complex mountainous areas, higher spatial resolution satellite estimates (e.g. MODIS) are indicated to better resolve mixed signatures such as forest and snow in complex terrain. The differences between modeled and measured SCA and SWE estimates may be a
mixture of the canopy influence on satellite SCA determination, variability in the SNOTEL SWE, and the model algorithm used to distribute climate data for calculation of a snowpack.

5. Conclusions

Experimental fractional SCA from AVHRR and ground-based SWE (with and without a vegetation correction) were evaluated against modeled snow fields in PRMS. The comparison was made under the assumption that modeled snow fields are reasonable because of PRMS’s previous success in simulating snowmelt runoff in the region. RESAC SCA and SWE were consistently low with respect to modeled SCA and SWE estimated from temperature and precipitation. The difference between the two fields depended on elevation and was different for the accumulation period versus the ablation period. An improvement to RESAC SCA and SWE (relative to modeled fields) was made by applying a canopy correction. When the RESAC snow fields were directly introduced into the model to replace modeled snow fields, they inevitably reduce model performance, and the negative impact progressively increases through the season. Since RESAC estimates were systematically low, water was discarded each time a substitution was made and there was an accumulating error in the water balance of the catchment. Although it was not possible to decisively determine which snowpack estimate was better in this study, if RESAC snow fields are to be used in a hydrologic model, it is clear that the model must be calibrated in way consistent with the measured input data.
Acknowledgements

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References


Table 1. Processed AVHRR SCA scenes for model updates.

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Table 2. Water balance (mm) and hydrograph fit for model runs (1995-2000).

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Figures

**Figure 1.** Elevation (USGS 30 m DEM) and land cover (USDA, 1992) for the Grande (panels a and b) and Black basins (panels c and d).

**Figure 2.** Canopy correction for the Black and Grande. The canopy factor was calculated on 2 March 1997 for the Black and 3 March 1996 for the Grande. The canopy factor was then applied to all 229 SCA acquisition dates.

**Figure 3.** Modeled (base) vs. measured (remote and veg correct) SCA and SWE for the Black basin over the whole time period (top) and 1998 (bottom). “Base” was the model run with no updates, “remote” was RESAC SCA and SWE, and “veg correct” was the canopy corrected RESAC SCA and SWE.

**Figure 4.** Modeled (base) vs. measured (remote and veg correct) SCA and SWE for the Grande basin over the whole time period (top) and 1998 (bottom). Values are the same as Figure 3.

**Figure 5.** Average normalized SCA differences ± standard error for the Black before April 1 (a) and after April 1 (b); and for the Grande before April 1 (c) and after April 1 (d). Values were calculated by subtracting the measured value from the model (base) value for each time step an update is available, expressed as the average value per 1-km$^2$ pixel within each 250-m elevation zone.

**Figure 6.** Average SWE differences ± standard error for the Black before April 1 (a) and after April 1 (b); and for the Grande before April 1 (c) and after April 1 (d). Values were calculated by subtracting the measured value from the model (base) value for each time step an update is available, expressed as the average value per 1-km$^2$ pixel within each 250-m elevation zone.
**Figure 7.** Cumulative simulated discharge (1995-2000) for Black (a), Grande (updates for all 229 dates) (b), and Grande (January 1 - April 1 updates, 116 dates) (c). Simulations were based on manually calibrated parameters and xyz distribution of climate forcing data. “Observed” was measured at the USGS gauge, “base” was the model run with no updates, “remote” used RESAC SCA and SWE, “remote SWE” used RESAC SWE and the model SCA, “filter” used RESAC SCA and SWE processed with a low pass 9-km² averaging filter, and “veg correct” used the canopy corrected RESAC SCA and SWE.

**Figure 8.** Discharge for the Black and Grande during 1998. Simulations were the same as Figure 7. Cooperative stations used for calibration provided climate data. Precipitation values represent events > 0.1 inches accumulation and updates shown had less than 50% cloud in the measured SCA AVHRR scene. SWE change was calculated as measured minus modeled so that negative values indicate a loss of SWE from the catchment.

**Figure 9.** Discharge for the Grande using updates only through April 1. Simulations were the same as Figure 7 and climate data were the same as Figure 8.
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