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Snow water equivalent interpolation for the Colorado River Basin from snow telemetry (SNOTEL) data

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[1] Inverse weighted distance and regression nonexact techniques were evaluated for interpolating methods 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 higher than average, average, and lower than average snow years. Because of the terrain effects, the regression techniques (hypsometric elevation and multivariate 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 multivariate techniques in order to preserve the point SNOTEL data. On the basis of root mean square error analysis and estimates of SWE volumes in different elevation zones for the entire basin and for subbasins 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. *INDEX TERMS:* 1863 Hydrology: Snow and ice (1827); *KEYWORDS:* snow water equivalent, SNOTEL, spatial interpolation, Colorado River

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1. Introduction

[2] Approximately 70–80% of the total annual runoff in the western United States 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 United States, *Osterberg* [1993] wrote that snow has a subconscious influence on the modern populations of the western United States; snow, even when not directly affecting an environment, builds to the allure of the wild and rugged nature of the west.

[3] To estimate snow quantities for the western United States, 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-km^2 resolution for the western United States [*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].

[4] Statistical methods have be used to interpolate SWE for large areas where there is limited variation in topographic relief [*Carroll et al.*, 1999], or for small basin 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 subbasin 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. As well, the search criteria associated with such a regression has not been evaluated. Multivariate 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.

[5] Various data sources have been used to develop the spatial estimates, including snow course measurements, snow telemetry (SNOTEL) snow pillow measurements,

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airborne gamma measurements and local fine-scale basin measurements. NOHRSC produces an operational SWE map for the entire United States (see http://www.nohrsc.nws.gov), 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.

[6] Nonexact 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 automatic 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.

[7] Kriging and cokriging, such as with elevation, have proven useful for smaller domains [e.g., *Carroll and Cressie*, 1996, 1997], however the selection of a model to fit a variogram cannot easily be automated. Authorized variograms can be selected, but at present the seasonal and interannual 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.

[8] 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-km^2 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 multivariate physiographic), and detrended regression-inverse weighted distance methods (with regression from both the hypsometric and multivariate 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 subbasins 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.

2. Study Area

[9] 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 km^2, an elevation range of 975–4260 m and an average elevation of 2150 m. The Lower Colorado has a drainage area of 346,000 km^2, 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 subbasins: Gunnison (20,500 km^2), San Juan (63,700 km^2), and the Salt-Verde (35,100 km^2) (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.

3. Data

[10] Snow course measurements have provided biweekly to monthly SWE at up to 2000 sites in the western United States. 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 United States, with approximately 240 operated around the Colorado Basin since 1991 (see *Serreze et al.* [1999] for a description of the stations and the data).

[11] 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 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 be 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 increments 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.

[12] 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 (Figures 2a and 2b).

4. Methods

4.1. SWE Interpolation Methods

[13] Four main interpolation techniques were employed at a grid resolution of 1 km^2: inverse weighted distance squared

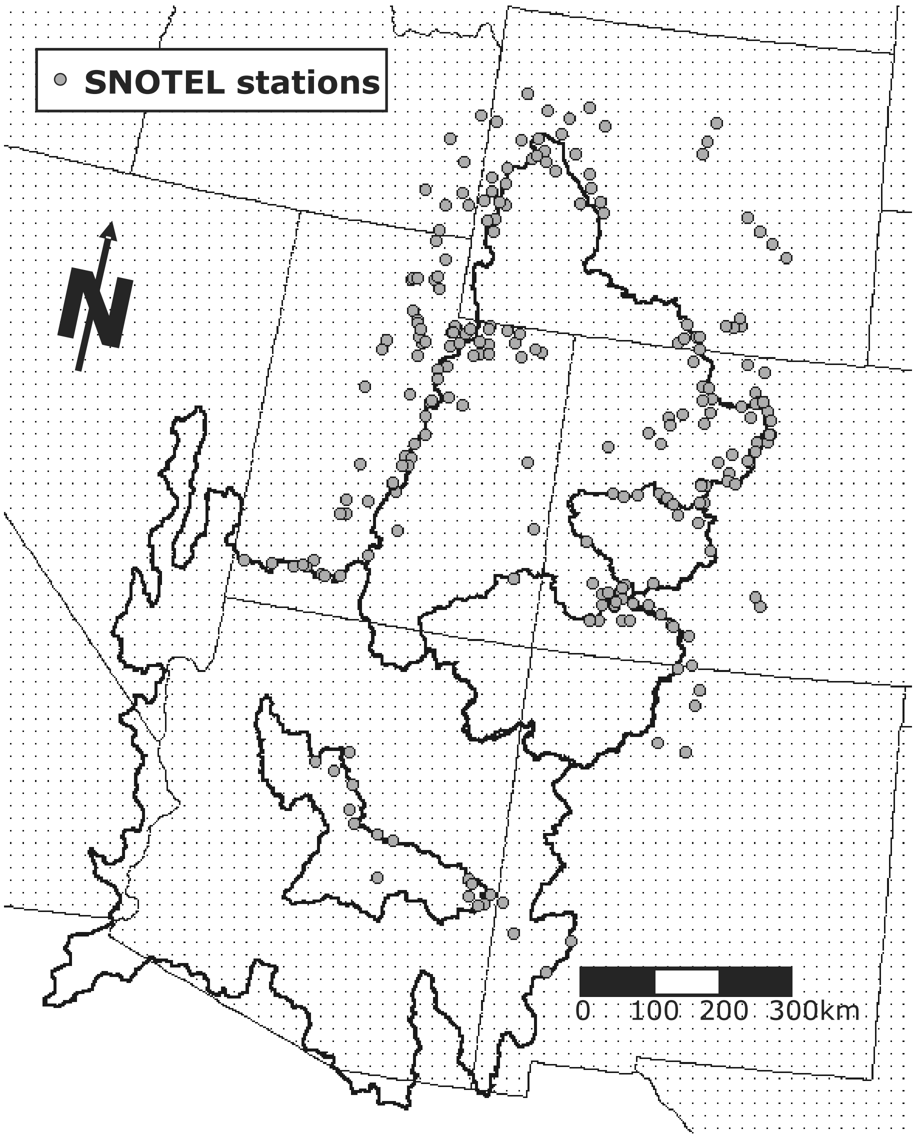

Figure 1. Location map.

(IDW), optimal distance averaging (ODA), hypsometric (HYP), and multivariate physiographic regression (MVR). As well, the hypsometric and multivariate 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.

[14] 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.

[15] 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.

[16] A linear multivariate 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

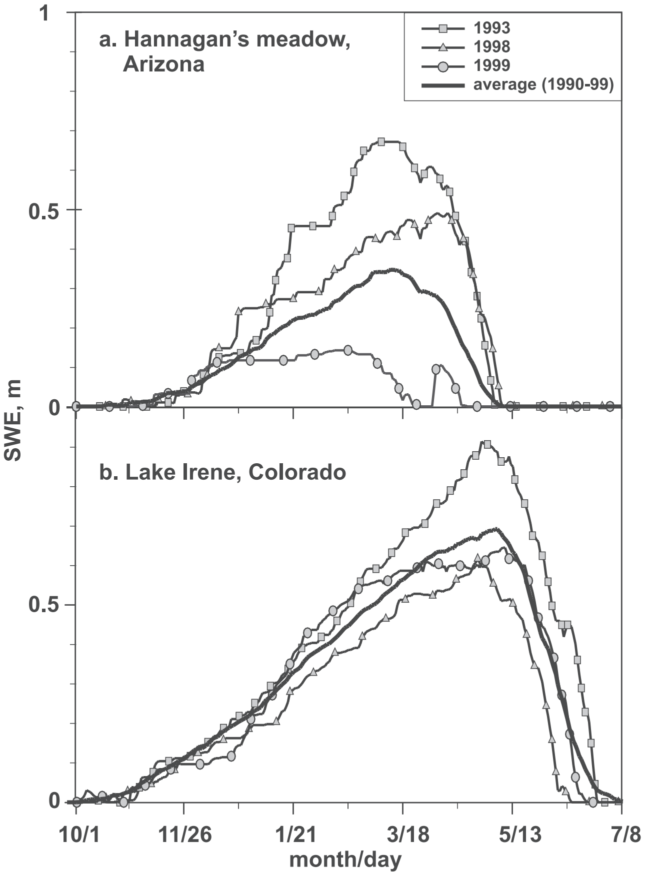

Figure 2. SNOTEL snow water equivalent for 1993, 1998, 1999, and the 1990–1999 average at (a) lower and (b) upper basin site.

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 by *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 three 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, 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 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 United States, 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 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] (see http://www.srsfia.usfs.msstate.edu/rpa/rpa93.htm), 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].

Table 1. Summary of Regression Parameters, Their Source, and Relative Importance of Each Parameter in the Regressions[a]

Variable Name	Source	Importance
Longitude	X from Natural Resources Conservation Service (NRCS) data converted to Albers	low
Latitude	Y component from above (NRCS data)	high
Elevation	Z from DEM	high
Local slope	sin slope (Δz) from 1 × 1 pixels	low
Local eastness	sin aspect (Δx) from 1 × 1 pixels	low
Local northness	cos aspect (Δy) from 1 × 1 pixels	low
West footprint slope	Δz from 5 column by 3 row pixels with pixel of interest at column 4, row 2	moderate
West footprint eastness	Δx for west footprint	low
West footprint northness	Δy for west footprint	low
South footprint slope	Δz from 3 column by 5 row pixels with pixel of interest at column 2, row 2	low
South footprint eastness	Δx for south footprint	low
South footprint northness	Δy for south footprint	low
Regional slope	Δz for 9 km swath around pixel	high
Regional eastness	regional Δx	low
Regional northness	regional Δy	low
W/NW/SW distance to ocean[b]	distance to ocean computed from west, northwest, and southwest	moderate
W/NW/SW barrier height[b]	elevation difference between maximum barrier in direction of ocean and pixel	high
W/NW/SW barrier distance[b]	distance from maximum barrier in direction of ocean to pixel	low
W/NW/SW shield height[b]	cumulative elevation increase between ocean and pixel	low
Forest density	U.S. Forest Service density maps from AVHRR imagery	moderate

[a]The standard USGS Albers projection was used to identify the relative latitude and longitude.
[b]The distance to the ocean, barrier height, barrier distance, and shield height were measured from the west, northwest, and southwest.

[17] The hypsometric regression and multivariate 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 multivariate 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 subbasin 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-km^2 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 test 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.

4.2. SWE Interpolation Search Parameters

[18] 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.

4.3. Error Evaluation

[19] A weekly time step from 29 December to 29 June 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.

[20] 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) was computed. 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 parameter 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.

[21] 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.

4.4. SWE Volume Estimates

[22] 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.

4.5. Method Selection

[23] 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 subbasins. 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.

5. Results

[24] 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.

[25] Among the four nonresidual methods, the hypsometric and multivariate regression techniques had the lowest RMSE in all 3 years (Figures 4a–4c), 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 multivariate 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.

[26] Without removing SWE estimates beyond the maximum snow extent, there is a significant difference between

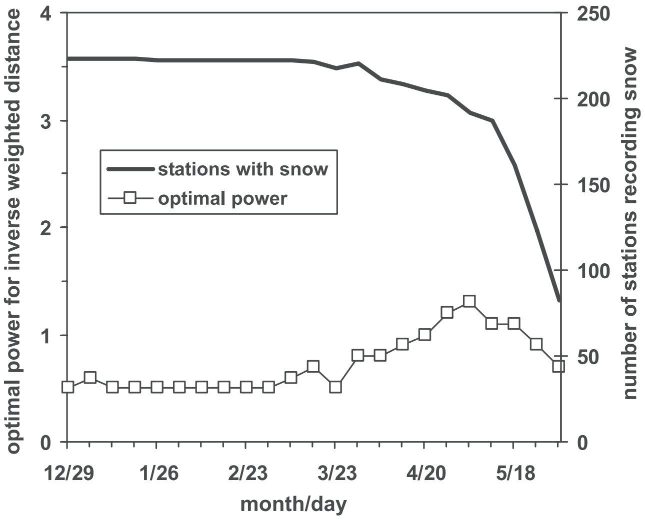

Figure 3. Optimal power for the inverse weighted distance as a function of time, with the number of snow telemetry (SNOTEL) stations recording snow, for the 1993 water year.

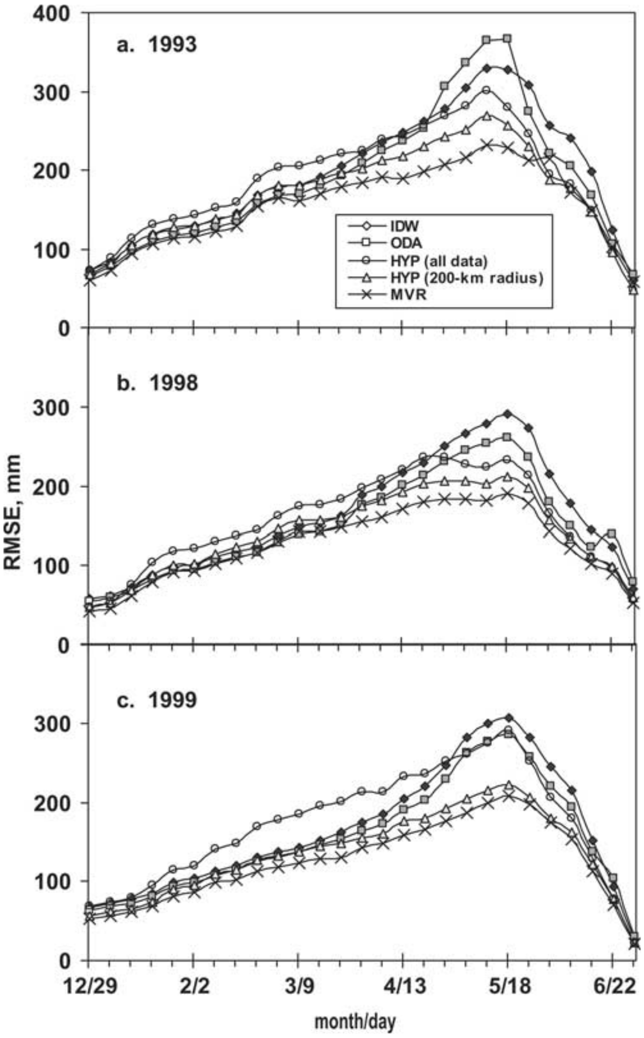

Figure 4. Root mean square error for the different interpolation methods using only SNOTEL data for 3 water years. See color version of this figure in the HTML.

Table 2. Average Yearly RMSE and Bias for the Different Interpolation Methods

		Interpolation Method				
Statistic	Year	IDW	ODA	HYP (200-km Radius)	HYP (All Data)	MVR
RMSE	1993	193.8	187.3	169.9	186.6	155.4
RMSE	1998	161.4	149.2	139.9	155.3	125.9
RMSE	1999	162.6	152.6	134.4	170.7	123.6
Bias	1993	−0.651	−0.428	−0.036	−0.184	−0.319
Bias	1998	−0.440	−0.184	−0.074	0.218	−0.009
Bias	1999	−0.519	−0.393	−0.013	0.164	−0.009

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 30 March 1993 as this roughly when peak accumulation occurs over all elevations across the entire basin.

[27] 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 (Figures 6a–6d). As illustrated in Figure 5, the inverse weighted distance approaches (IDW and ODA) provide larger SWE volume estimates at lower elevations (Figures 6a and 6b) and smaller estimates higher elevations (Figures 6c and 6d). These patterns were also observed for 1998 and 1999. The trends in the SWE volumes were similar for the Gunnison subbasin for 1993 (Figures 7a–7d) and the two other study years. However, for the Salt-Verde subbasin (Figures 8a–8c), 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.

[28] Increased search radii increased the RMSE for all study years, especially 1999 (Figure 9), as SWE increased. For 30 March 1993, the differences in SWE were only observed at the lowest and highest elevations, where SWE

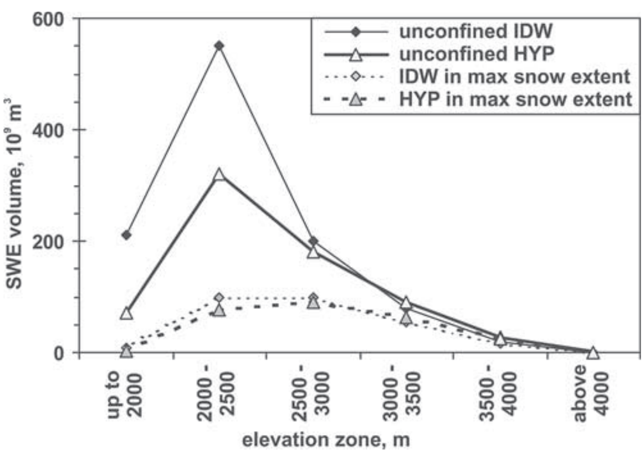

Figure 5. Variation in SWE volume per elevation zone for the IDW and HYP interpolation methods for 30 March 1993 for the entire domain interpolation and for the only the snow covered area defined by the AVHRR-derived maximum snow extent. See color version of this figure in the HTML.

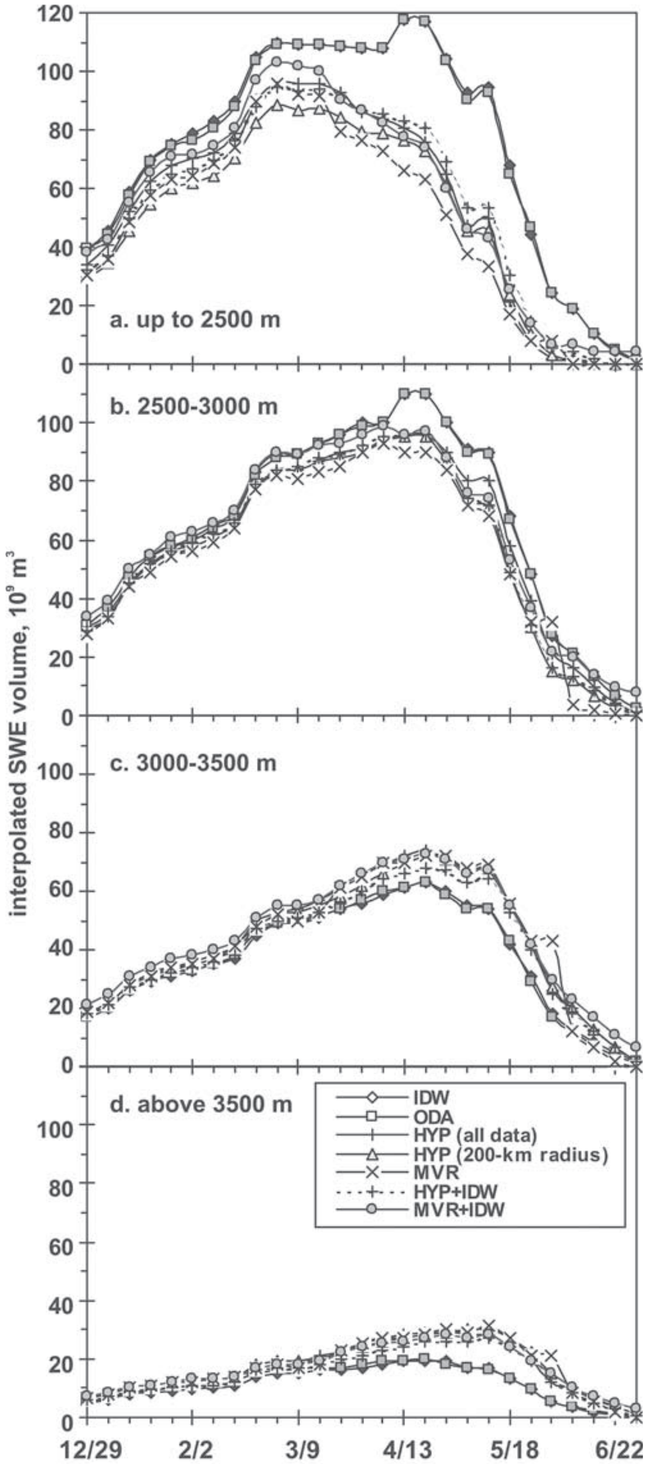

Figure 6. SWE volume limited to the maximum snow extent over the 1993 time series for the entire Colorado River basin for various elevation ranges. See color version of this figure in the HTML.

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).

6. Discussion

[29] The spatial variation of SWE increases as the snow season progresses. The plots of RMSE for each of the three study years (Figures 4a–4c) 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

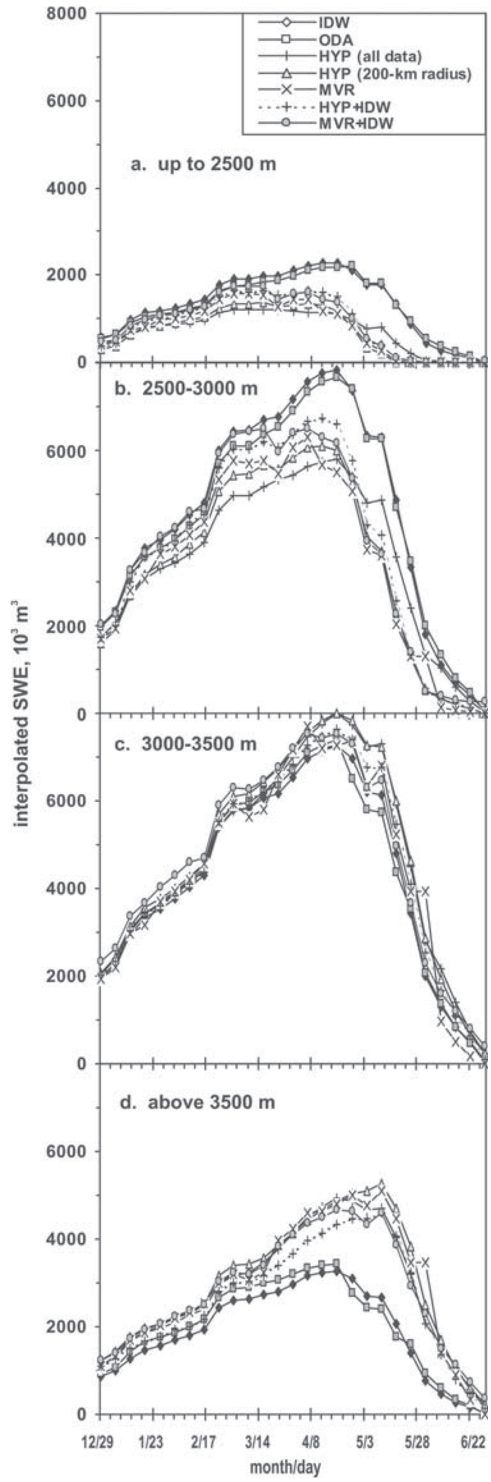

Figure 7. SWE volume limited to the maximum snow extent over the 1993 time series for the Gunnison River basin for various elevation ranges. See color version of this figure in the HTML.

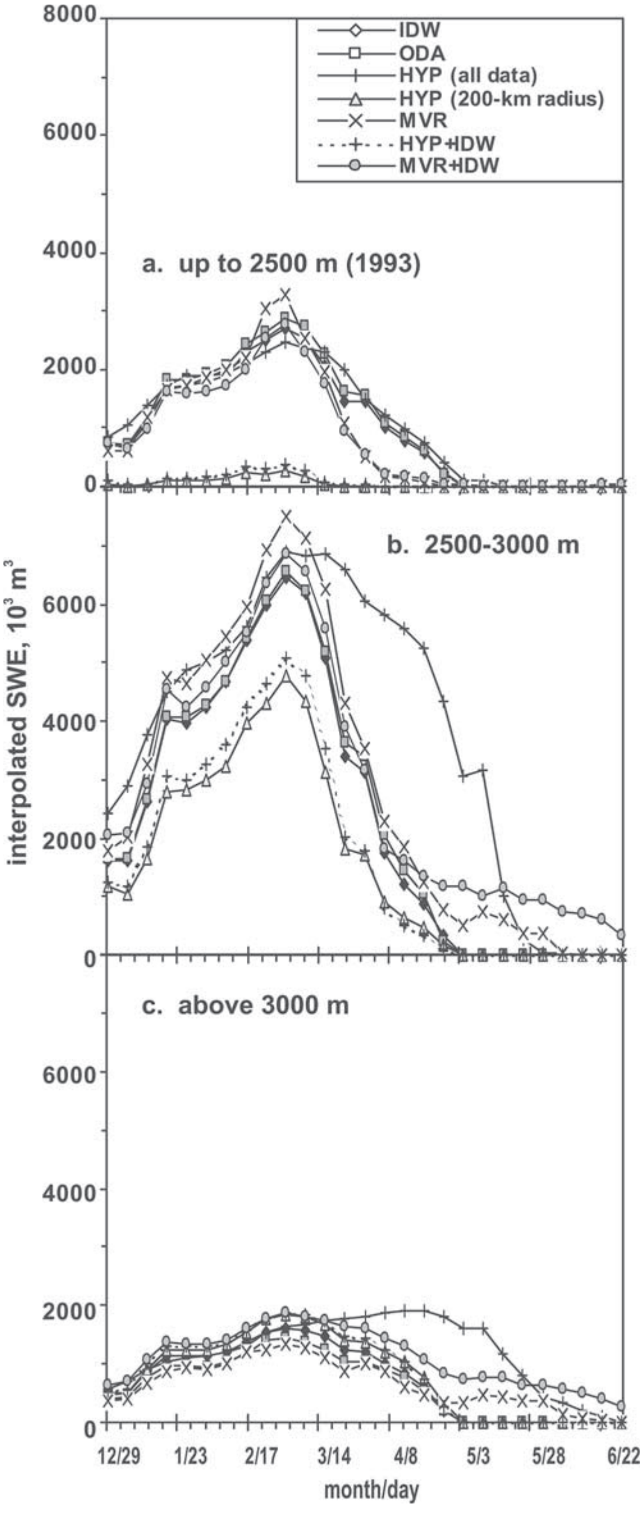

Figure 8. SWE volume limited to the maximum snow extent over the 1993 time series for the entire Salt-Verde River basin for various elevation ranges. See color version of this figure in the HTML.

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 27, 17, and 23 May 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 (e.g., Figures 2a and 2b). As well, the snowpack is less continuous at lower elevations due to an earlier onset of melt. The earliest melt-out is 29 March, 30 March, and 9 February for the three years.

[30] 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 (Figures 6a–6d).

[31] 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 multivariate 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–6d). While this was consistent for the Gunnison subbasins (Figures 7a–7d), the MVR estimates were substantially larger than the HYP estimates for the Salt-Verde (Figures 8a–8c) since the entire Colorado domain was used to generate the multivariate 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.

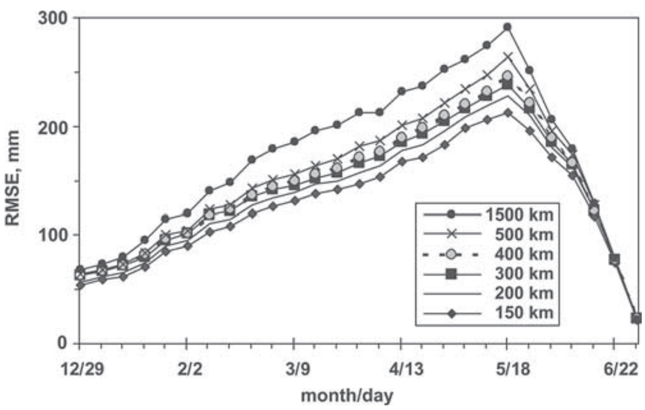

Figure 9. Root mean square error for different search radii over the entire Colorado River basin for 1999. See color version of this figure in the HTML.

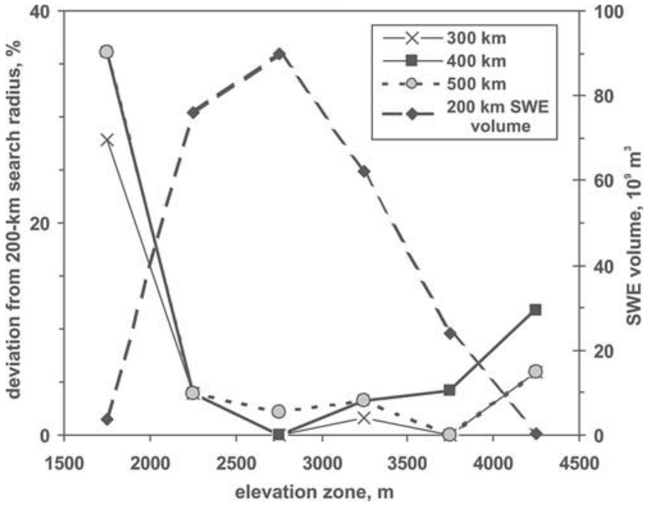

Figure 10. SWE volume of variable search radii (expressed as percent difference from 200 km search radius) per elevation zone for 30 March 1993. See color version of this figure in the HTML.

Although computational significant, multivariate regression using a moving search radius, or at least subbasin 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).

[32] 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 multivariate 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.

[33] 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. Snow course and airborne gamma SWE data should be introduced into the interpolation.

[34] 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 (Figures 6a–6d) 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 multivariate approach. The search radius would be at least 400 km since a minimum number of stations (number of variables in the regression plus one) is required to develop a multivariate 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.

[35] 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.

7. Conclusions

[36] The regression (HYP and MVR) interpolation techniques are superior to the distance weighted approaches (IDW and ODA) for interpolated SNOTEL data. The multivariate 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 multivariate 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

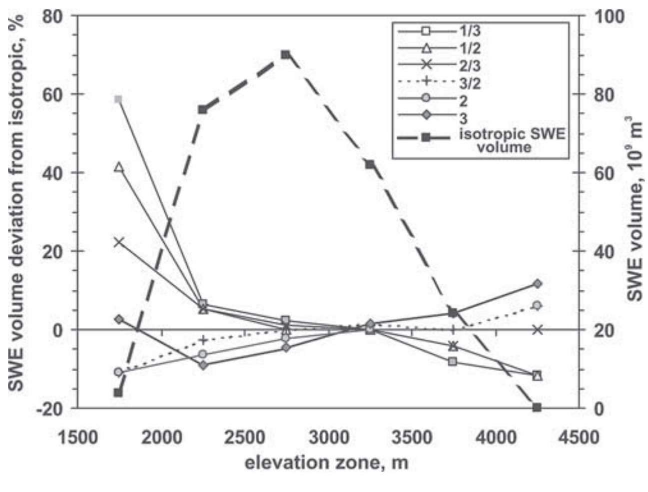

Figure 11. SWE volume of variable anisotropy factors (expressed as percent difference from an isotropy search radius) per elevation zone for 30 March 1993. See color version of this figure in the HTML.

radius, instead of a single regressing equation (HYP all data) should be used to develop SWE maps.

[37] 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 subbasins for computation, and the use of multiple linear regressions.

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