University of Washington
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EVALUATION OF SNOWMELT FORECASTING METHODS

Dennis P. Lettenmaier
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Water Resources Series
Technical Report No. 68
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ABSTRACT

Snowmelt runoff forecast accuracy has significant economic implications for water resources management, most importantly for hydroenergy production and irrigated agriculture. In recent years, conceptual simulation models of the snow accumulation and ablation and rainfall-runoff processes have been advocated as a means of improving seasonal runoff forecast accuracy, through what has been termed extended streamflow prediction. These models form an alternative to the simpler, more widely used storage index models. In this work, retrospective forecasts were made for two western Washington rivers, the Cedar and the Cispus, using the National Weather Service snowmelt and soil moisture models as representative of the state of the art of conceptual models, and the Hydrometeorological model of Wendell Tangborn as representative of the more sophisticated of the storage index models.

Analysis of approximately 20 years of forecasts for both basins indicated that the conceptual models performed no better than the storage index model, despite greatly increased logistical requirements. An additional analysis was conducted for four years of extreme low runoff which also showed no conclusive differences in forecast accuracy for the two models. Calculations were performed to determine the limiting forecast accuracy for the conceptual model conditioned on the statistics of monthly simulation errors. The results showed that simulation error, which is largely dependent on data network density, probably limits forecast accuracy, especially for forecasts late in the runoff season. This implies that significant improvements in forecast accuracy for conceptual models may not be possible given current data limitations for many mountainous watersheds.

Although the results may not be encouraging for advocates of conceptual models, two situations were identified which may warrant their use. The first is in applications where only short record lengths exist for the hydrometeorological stations (e.g., less than 10-15 years). In this case, storage index model parameter error may become large enough that conceptual models, which can be calibrated with much shorter record lengths, will be preferred. The second situation assumes adaptation of the current extended streamflow prediction framework to incorporate feedback in the form of runoff and snowcourse measurements to reduce the effect of simulation error.

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Chapter 1

Introduction

This report describes work conducted as part of an ongoing investigation of streamflow forecasting methods, with particular emphasis on forecasting of seasonal snowmelt runoff. Earlier results have been reported in Lettenmaier and Waddle (1978), Lettenmaier (1978), and Lettenmaier and Garen (1979). In the earlier work, a seasonal snowmelt runoff forecasting model which utilizes low elevation precipitation and snow cover data was developed as a modification of the Hydrometeorological (HM) model of Tangborn (1977). In addition, Lettenmaier and Waddle (1978) reported an attempt to implement the Sacramento (Burnash et al., 1973; Burnash and Baird, 1975) snow accumulation and ablation and soil moisture accounting models which have been successfully used to forecast seasonal snowmelt runoff in the California Sierra Nevada range. While the soil moisture accounting model was found to perform adequately in the test basin (the Cedar River, also used in the present work) the snow model did not give satisfactory results, apparently as a result of differences in the melt process between California and the Pacific Northwest. In this work, we have retained the Sacramento soil moisture accounting model, but have made use of Anderson's (1973) snow accumulation and ablation model. The Anderson model has been extensively tested by the National Weather Service Hydrologic Research Laboratory in a number of basins in varying climatic regions, including the Pacific Northwest. We have implemented the model on the University of Washington CDC computer and have developed a data handling system to prepare input data for the model. The model has been tested on two Western Washington drainages; the Cedar River, which provides approximately 70% of the domestic water supply for the City of Seattle, and the Cispus River, a tributary of the Cowlitz River which provides a substantial part of the hydroelectric power generated by Tacoma City Light.

The Cispus River lies in an area impacted by ash fallout from the May 18, 1980 and subsequent eruptions of Mount St. Helens. Runoff modeling of this basin was part of a project reported elsewhere (Lettenmaier, et al., 1980) to assess impact of the eruption on flood hazard increase of nearby communities. Although a slightly different calibration of the model was used for flood hazard evaluation, much of the data collection and other logistical effort in the Cispus study was carried out simultaneously.

Background

In the western U.S., most major streams originate in mountainous areas which receive much higher annual precipitation than do lowland areas. At the elevations which contribute most heavily to runoff, precipitation occurs primarily in the winter months as snow. In the arid interior of the West, developers of the earliest water projects saw the potential for use of winter snow course measurements as indicators of runoff in the spring and summer melt period. By the 1930's, a network of snow course observation stations had been established, which was the predecessor to the cooperative program presently managed by the U.S. Soil Conservation Service. With the expansion of the data base, analytical methods of forecasting seasonal runoff were developed. The earliest methods, many of which are still in use, made use of indices of runoff, such as snow course readings, winter precipitation at low elevation stations, soil moisture measurements, extent of snow cover, etc. Statistical methods were later brought to bear on the index relationships, resulting in various forms of regressions relating forecast period runoff with the index variables.

With the advent of the digital computer, the level of detail which could be considered by numerical models of snowmelt and runoff physics was vastly increased. This prompted analytically oriented hydrologists to develop simulation models of the runoff, and, later, snow accumulation and ablation processes. These models, often referred to as conceptual simulation models, attempt to trace the fate of incident precipitation through several zones which represent a conceptualization of the soil column, to its ultimate fate as streamflow or evaporation. Similarly, snowmelt (snow accumulation and ablation) models attempt to simulate the history of water storage in a snowpack, including the melt process, producing a simulated record of effective precipitation, consisting of rain on bare ground and snowmelt. This effective precipitation (also referred to as psuedo precipitation) record is used as input to a soil moisture accounting model.

Conceptual simulation models are generally data intensive and require a certain amount of experience of the user for successful implementation. They have been used for a variety of purposes, of which flood forecasting is probably the most important. However, they have also been used for seasonal runoff forecasting, notably by the California joint State-Federal River Forecast Center and the National Weather Service Hydrologic Research Laboratory. The National Weather Service refers to use of its family of forecast models for seasonal forecasting as extended streamflow prediction. The advantage of use of conceptual models in such a framework is that they allow explicit consideration of such factors as antecedent soil moisture, not usually included in index models. They also allow convenient exploration of alternate scenarios. The Sacramento River Forecast Center, for example, was able to provide streamflow forecasts during the 1976-77 drought which were considerably more accurate than those achieved using index methods.

In an attempt to achieve a balance between logistical requirements and the desirability of including some representation of physical causality in seasonal forecasts, Tangborn (1977) developed the HM model referred to earlier. This model represents forecast season runoff as the difference between total seasonal precipitation incident on the watershed and the sum of winter season runoff and losses from the system. The relationship can also be expressed in terms of basin storage, in which forecast season runoff is taken to be winter storage less losses plus forecast precipitation. The required coefficients are estimated by regression as are the coefficients in the index methods. The primary advantage of this model is that, as the result of inclusion of an effective storage component, it is able to reflect soil moisture/runoff interactions, which are especially important in extreme years, in a rather simple manner. Lettenmaier and Garen (1978) found, particularly for the Salt River in Arizona, that the most accurate runoff forecasts were achieved in extreme high and low runoff years. These are the conditions under which the index methods perform most poorly; the relationships used to link the indices with runoff are usually linear and are most in error when conditions are farthest from normal It should also be noted that the worth of an accurate forecast is highest under extreme conditions, particularly droughts. To the practitioner, forecast worth must be the ultimate justification for comparisons of the type reported here; for this reason a brief description of estimates of forecast worth follows.

Worth of Streamflow Forecasts

Improvement of runoff forecast accuracy is of practical importance only if it has some impact on water utilization. The support of water users for water forecasting programs may be seen as some indication of the worth of forecasts. For instance, the U.S. Soil Conservation Service, in considering possible change to its snow survey and water supply forecasting program, conducted a survey during 1979-80 of users of the program. Among various options ranging from elimination of the program to continuation of the existing program and possible program expansion, a large majority supported continuation and/or expansion of the present program. Of course, there is no direct cost to the users for the SCS service, so it is not possible to employ a willingness to pay criterion to assess the worth of the information. However, various attempts have been made to evaluate forecast worth. Several of these were reviewed by Lettenmaier and Waddle (1978). Recent work by Castruccio, et al. (1979) provides estimates of the worth of forecast accuracy improvements throughout the Western U.S. Although this work attempted to establish the worth of satellite snow cover observations in improving forecast accuracy, the results are general and are worth inclusion here to establish an economic perspective.

Castruccio, et al. identified five water uses which might be impacted by water supply forecasts. Of these, two, hydroenergy and irrigated agriculture, are by far the most economically significant. Table 1a summarizes the potential direct and indirect benefits of runoff forecasts identified by these authors for the two most important water uses. In the cited work, the value of snowmelt runoff for both hydroenergy and irrigation was identified as an upper bound on forecast worth, and the impact of uncertainty on the worth of snowmelt runoff estimated. The methodology used is not of importance here, however, the results (Table 1b) are worth reviewing. These results are computed on the basis of a 6 percent improvement in forecast accuracy. This improvement level is not of immediate concern (in fact, the 6 percent is the estimate arrived at as improvement attributable to satellite snow cover observations; it is the

Table 1a. Potential Benefits of Improved Runoff Forecasts (from Castruccio, et al., 1979)

Irrigated Agriculture

Direct Benefits:
(a) Increase in net farm income due to lower production costs
(b) Increase in net farm income due to improved crop selection
(c) Improvements in operational efficiency of in-place irrigation projects

Indirect Benefits:
(a) Increases in net income to agriculture industry suppliers
(b) Reduction in food cost to populace
(c) Reduction in energy required to provide irrigation

Hydroenergy

Direct Benefits:
(a) Cost savings due to improved mix of hydroenergy and thermal energy
(b) Value added by improved scheduling efficiency at multiple sites
(c) Improvements in plant operating efficiency due to improved power production scheduling

Indirect Benefits:
(a) Conservation of fossil fuel supplies
(b) Reduction of necessity for construction of high cost, thermal plants

Table 1b. Estimated Annual Benefits to Irrigated Agriculture and Hydroenergy of 6% Improvement in Seasonal Runoff Forecast Accuracy (from Castruccio, et al., 1979)

	Irrigated Agriculture		Hydroenergy	
	Total Benefits[a]	Benefit Per Irrigated Acre[b]	Total Benefits[a]	Benefit Per KwH Generated[c]
Pacific Northwest	8.2	0.85	3.8	0.03
California	5.6	1.41	1.9	0.06
Missouri	7.1	1.13	1.0	0.17
Great Basin	2.8	1.58	0.1	0.18
Upper Colorado	1.1	0.87	1.1	0.20
Arkansas	0.9	1.70	0.0	0.7
Rio Grande	1.6	4.02	0.1	1.03
Lower Colorado	0.8	8.95	2.1	0.46

[a] millions of dollars [b] dollars per acre [c] mils per KwH

feeling of the present writers that this estimate is tenuous and probably not statistically significant); what is significant is the potential improvements and the associated unit economic benefits.

In the Castruccio, et al. results the Pacific Northwest (defined as the Columbia basin in addition to the Puget Sound drainage basin) has the highest potential benefits for both irrigated agriculture and hydroenergy. This reflects the large amounts of water use in the Northwest for these activities; the unit improvements (e.g., mils/kwH or $/acre) are low. The low unit benefits result from the low variability of streamflow in the Northwest as compared with other regions. The high total potential benefits do indicate the extent of water use which could be affected by improved forecasts, and suggests that the Northwest has a special interest in any improvements in forecast accuracy which can be achieved at reasonable cost.

These results should serve to indicate the potential economic benefits of research, such as that reported here, which is directed at improvements in forecast accuracy. A reasonable question is the potential for forecast accuracy improvements, i.e., how much better can be done in applied situations given typical data availability? This section is concluded with a brief comment on this question.

Streamflow forecast accuracy is dependent on a number of factors of which this research considers only one, the forecast model itself. Other factors include watershed characteristics (steepness, aspect, geographic location), climatic conditions, runoff characteristics, such as infiltration rate and subsurface moisture storage potential, as well as data availability (location of stream gages, snow courses, and precipitation gages). Clearly, watershed characteristics cannot be controlled by the forecaster, and, in the short run, neither can data availability. Based on earlier work cited above, it appears possible in some cases where adequate data are available and present methods are relatively crude (e.g., index method) to achieve forecast accuracy improvements in excess of 25%. More commonly, improvements in the range of 10% appear to be a more reasonable expectation. It should be emphasized that these estimates are based only on the judgement of the authors; they do, however, give some indication of the magnitude of improvement which might be possible. Results given later in this report may also prove helpful in assessing potential accuracy improvements.

One final comment regarding the manner in which forecast accuracy, and improvements are measured, is appropriate. A number of past comparative studies of forecast accuracy (often initiated as justification for a new model) have used measures such as the correlation between forecasted and observed runoff and mean square error (MSE) as accuracy measures. Often, these statistics are calculated for the same period of record as that used to estimate parameters. When this is done, the statistics reflect only the quality of calibration, and give no indication whatever as to model performance (forecast error). It is well known in statistics that the number of degrees of freedom of a statistical model is the sample size less the number of parameters estimated from the sample, and that the variance of an estimated parameter is inversely proportional to the degrees of freedom. It is possible, if enough parameters are used in a model, to achieve "exact" calibration with infinite parameter variances. Thus, while the model would appear to give an excellent "fit" to the data, it would be worthless for forecasting purposes. Consequently, measures of calibration error cannot be considered to give a valid indication of model accuracy. The best approach to assessing forecast accuracy is the split sample method, in which the data are partitioned with parameter estimates obtained from one subset and forecasts made on an independent subset. This is the approach used here.

It is worth noting that, when subjected to a split sample test, many claims of accuracy improvements cannot be sustained. Further, implementation of a split sample test can be difficult, particularly in the case of conceptual simulation models which have large data requirements. There is also the problem of sample size; the mean square error (MSE), for instance, of forecasted runoff must be treated as a random variable, hence comparison of MSE's for alternate models should be considered in a hypotheses testing framework. The mere existence of differences makes no statement as to their statistical significance, which is a function of sample size. Taken together, these considerations lead us to suggest that, although economically important, the magnitude of potentially verifiable forecast accuracy improvements should realistically be viewed as modest.

Objectives

Given the economic significance of forecast improvements, the difficulty of assessing these improvements statistically, and the range of forecast models which might be used, the forecast user is faced with a difficult choice in model selection. Generally, the models whose claimed accuracy is highest are the most complex, e.g., conceptual simulation models. Although index methods remain in wide use, most modelers would agree that they are limited, especially under extreme conditions, and that improvements are possible without greatly increasing complexity. For this reason, and because of previous comparative tests demonstrating its applicability to a number of basins, the HM model (Tangborn, 1977) as modified by Lettenmaier (1978) is taken as the baseline for comparison.

The principal objective of the work reported here was to assess the viability of a conceptual simulation model (specifically consisting of Anderson's (1973) snowmelt model and the Sacramento (Burnash, et al., 1973) soil moisture accounting model; however, wherever possible results will be considered as relating to the general model type, rather than the specific models, whose performance has been verified elsewhere) in an extended streamflow prediction application. Of particular interest are data requirements, computational requirements, flexibility, ease of use, and forecast accuracy.

The comparisons are carried out for two west-slope Cascade Mountain drainages, the Cedar, which represents, in comparison to other Northwest drainages, a data-rich situation, and the Cispus River, which represents a more common, data-scarce situation. These two basins, in addition to providing a contrast in terms of data availability, are of practical significance as noted above. The Cedar River results, discussed in Chapter 2, were obtained before the Cispus modeling was begun. The Cispus was selected in part because of its importance in an ongoing study of runoff changes in the vicinity of Mt. St. Helens (Lettenmaier, et al., 1980) during which several changes were made in the models used. These changes, and an assessment of their significance for extended streamflow prediction, are discussed in Chapter 3.

Chapter 2

CASE STUDY 1: CEDAR RIVER

The Cedar River watershed (Fig. 1) drains an area of approximately 186 mi^2 of the west slope of the Cascade Mountains southeast of Seattle, WA. It provides about 70% of the mean annual inflow to Lake Washington, a large (35 mi^2) lake lying within the Seattle metropolitan area. Approximately 2/3 of the basin comprises the Seattle city watershed, and is closed to public access. Chester Morse Reservoir, which lies entirely within the City watershed, provides storage which is used to meet about 70% of the water supply requirement for the Seattle metropolitan area. This reservoir is a natural lake (formerly Cedar Lake) whose storage capacity is augmented by a crib dam near the natural outlet (1905), and a higher masonry dam approximately one mile downstream (1916) which provides a secondary storage pool and is capable of raising the reservoir level several feet above the crib dam. However, the effectiveness of the resulting secondary storage is limited by seepage losses, which become quite high when the reservoir pool level is raised to the level of the crib dam. Consequently, the masonry dam is used primarily to provide auxiliary storage for flood protection.

In addition to the seepage problem, several other important considerations enter into operation of the Cedar River system. Among the most important operating constraints are instream flow requirements for fisheries protection and enhancement, and constraints on fluctuations of the level of Lake Washington, to which the Cedar River provides about 70% of the average annual inflow. From an operating standpoint, Chester Morse Reservoir is linked with the Tolt River system, approximately 30 mi to the north for the purpose of meeting Seattle water supply requirements. The Cedar River system also has a

CEDAR WATERSHED

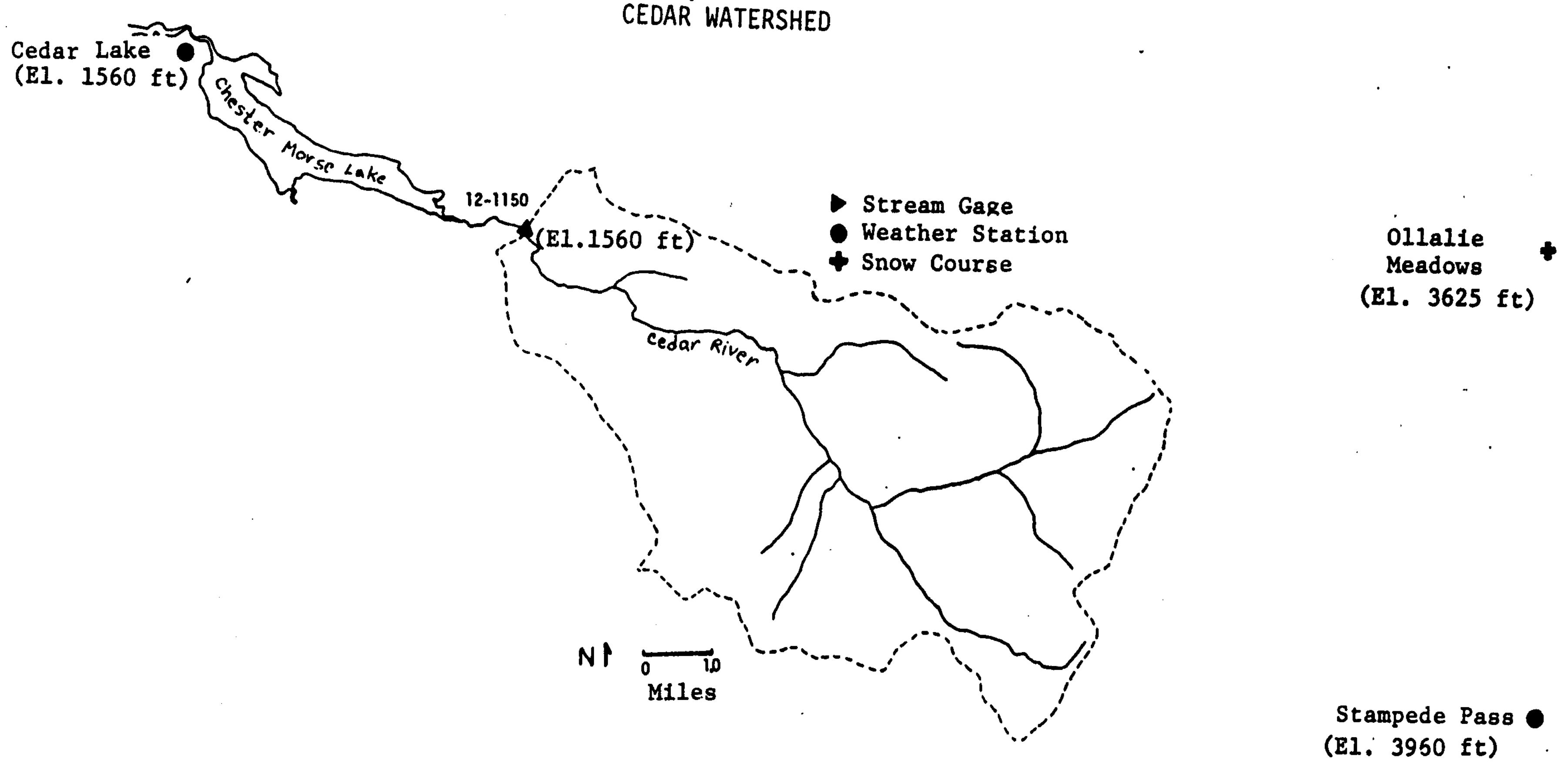

Figure 1. Cedar River Watershed including precipitation gage, snow course and stream gage sites.

small electrical power generating capacity, which may, however, be increased in the future. Draper, et al. (1981) have found that the instream flow requirements on the Cedar and Tolt River systems, which are largely related to fisheries concerns, have a critical effect in limiting system yield. As an aside, the fisheries requirements are related to a large sockeye salmon run, which is not native, but was transplanted from the Baker River, about 100 mi to the north, when that river was blocked to migration of the natural run by construction of a power generation reservoir in the 1920's. Miller (1976) has conducted a datailed study of the Cedar River sockeye run and associated instream flow requirements, with implications for water supply yield.

Given these conflicting management requirements, operation of the Cedar River system is a complex problem. The active storage capacity of Chester Morse Reservoir is small (in the vicinity of 10% of the mean annual runoff) so a premium is placed on accurate estimation of spring and summer runoff. In the upper part of the watershed (above Chester Morse Reservoir), most runoff is derived from melting of the snowpack. The elevation of the watershed ranges from about 1600 feet to 5400 feet. Above about 3000 feet, most precipitation in the November-April season (which accounts for about 2/3 of the annual total), occurs as snow. This offers the potential for reasonably accurate forecasting of spring and summer runoff by late winter, when most of the subsequent runoff is stored in the snowpack or as soil moisture.

Model Implementation

In this study, runoff forecasts were made for the Cedar River near Cedar Falls (USGS station 12-1150). Although the drainage area above this gage is only about 41 mi^2, a relationship has been developed (Howard, 1977) to index total inflow to Chester Morse Lake to the runoff at this gage. Our emphasis here is on evaluation of a forecasting method, rather than providing operational forecasts. However, this indicates that the forecast point selected does have practical significance.

The models used in this study have been well documented elsewhere (e.g., Anderson, 1973; Burnash, et al., 1973; Peck, 1976; Lettenmaier and Waddle, 1978; Parkinson, 1979) and so are not described in detail here. The conceptual models used, specifically the National Weather Service (NWS) snowmelt and runoff models, require considerably more effort in data acquisition and preparation, as well as calibration and verification, than does the simpler storage accounting (modified HM) model. For this reason most of the preliminary discussion here concerns the conceptual models, and some aspects of their implementation.

In many rainfall-runoff model applications, the most important errors occur in estimation of the input, specifically precipitation, and, where applicable, snowmelt. Problems typically encountered in determining precipitation inputs are sparseness of stations, errors in data collected at the stations available (e.g., bias and variability in rainfall catch efficiency, and missing or erroneous data reporting). These problems are particularly severe in mountainous watersheds, where natural variability of precipitation is high, and, due to difficulties in accessability, data collection stations tend to be sparse, especially at high elevations. Figure 1 shows the location of meteorological and snow course stations in the vicinity of the watershed being modeled. Although none of the stations lie within the watershed being modeled, the Cedar Falls station is in the Cedar River watershed downstream of the forecast point, and the Stampede Pass station is within 10 mi. of the basin centroid. The Stampede Pass station is also the only manned National Weather Service station at high elevation in the Cascade Mountains.

Precipitation records at hourly increments, as well as daily snow water equivalent (after 1965) and daily temperature maxima and minima are on record for this station. The Cedar Falls station also has hourly precipitation and daily temperature maxima/minima. No other stations were felt to lie close enough to the basin to warrant inclusion in the model. As will be noted later, and particularly in Chapter 3, the daily snow water equivalent record at Stampede Pass is very useful in calibration. In most mountainous watersheds, snow course data are available at best on a monthly or biweekly time step. The availability of hourly precipitation data, which can be aggregated to six hour totals, is another advantage not enjoyed in the other example application (Chapter 3).

The basin was divided into four elevation zones by examination of a hypsometric curve of the basin (Fig. 2). Anderson (1973) recommends use of a smaller number of zones (two, where possible) but the peculiarities of Pacific Northwest mountain climatology, with mostly rain at low elevations and mostly snow

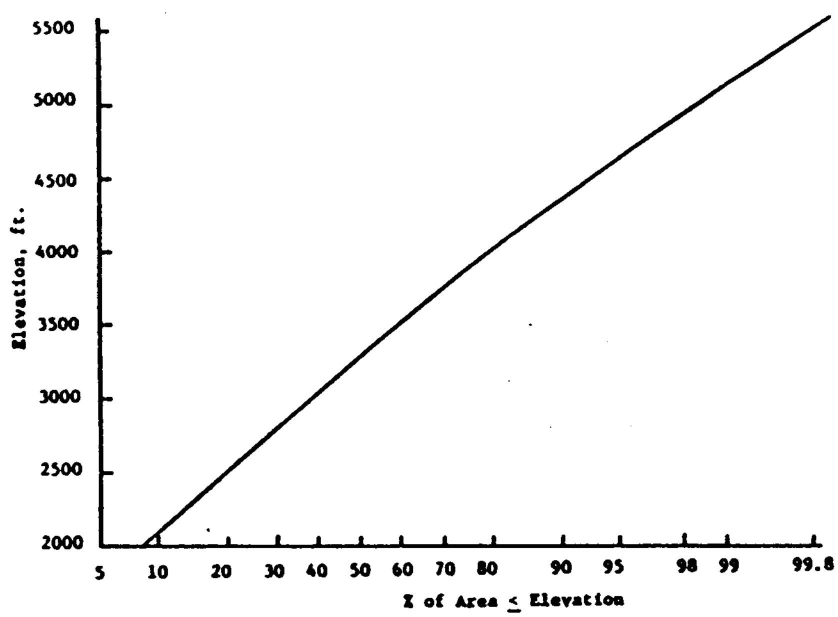

Figure 2. Hypsometric Profile of Cedar River Basin Above USGS Gaging Station No. 12-1150 Near Cedar Falls.

at higher elevations, dictates use of a larger number of zones to accurately capture the snow-rain division. The elevation zones used, and areas of each, are given in Table 2.

Table 2. Elevation Zones, Cedar River

	Elevation (ft)				
Zone	Maximum	Minimum	Mean	Area, mi^2	Per Cent Total
1	2532	1560	2046	9.0	22
2	3505	2532	3019	16.4	40
3	4477	3505	3991	12.7	31
4	5450	4477	4964	2.9	7

Precipitation for each zone was estimated by interpolating the Cedar Falls and Stampede Pass records linearly by elevation. Six hourly temperature breakdowns were computed using the relationship with daily maxima and minima recommended by Anderson (1973).

Missing or misrecorded data are always a problem in simulation modeling, particularly with the large volumes of data involved in simulating runoff on a daily time scale for a period of many years. For the two stations of interest, temperature data were missing for a total of 56 occurences (maxima or minima) at Cedar Lake and 12 occurences at Stampede Pass. There were 60 occurences of missing precipitation at Cedar Falls in the 1949-75 period of record, including the entire months of October and November, 1967; January, 1969, July, 1972, and June, 1974. There were no missing precipitation observations at Stampede Pass. Missing observations for both precipitation and temperature were estimated using records for other nearby stations, consistent with recorded observations, at whichever station in the Stampede Pass-Cedar

Falls pair had an observation for the day in question. Since most of the missing data were for Cedar Falls, a low elevation station, it was a relatively straightforward matter to find comparable stations for estimation of missing data. Temperature data were filled in by inspection of records for similar sites, since no more than five consecutive days were ever missing. Precipitation data were filled in using a comparable station (Landsburg, located in the lower Cedar River basin about 10 mi west of Cedar Falls, was used in most cases) and scaling the data by the ratio of the historic means for the month in question. In all cases, daily total precipitation for the missing stations was estimated, then disaggregated to six hourly totals using the same hourly distribution as was observed at Stampede Pass, assuming an average six hour time of passage for storms.

The initial calibration for the snow model was made by comparing zone 4 predicted snow water equivalent with the snow water equivalent record at Stampede Pass, which is at approximately the same elevation as the midpoint of zone 4. These calibrations were made for water years 1965-69, the results of which are shown in Figs. 3(a)-(e). In most cases, the model traces the Stampede Pass data well. In fact, there is no reason to expect the model prediction to match the recorded values precisely, since the model attempts to predict average snow water equivalent over the elevation zone, which will generally differ from measurements made at any point with the same elevation as the zone average. For this reason, an attempt was made only to match the beginning and ending date of snow accumulation, and approximate peak accumulation. Although additional snow course stations, maintained by the Seattle Water Department, exist at low elevations which might have been used for calibration of zones 1, 2, and 3, the readings at these sites were found to be highly variable, and the two measurements per year at these stations were

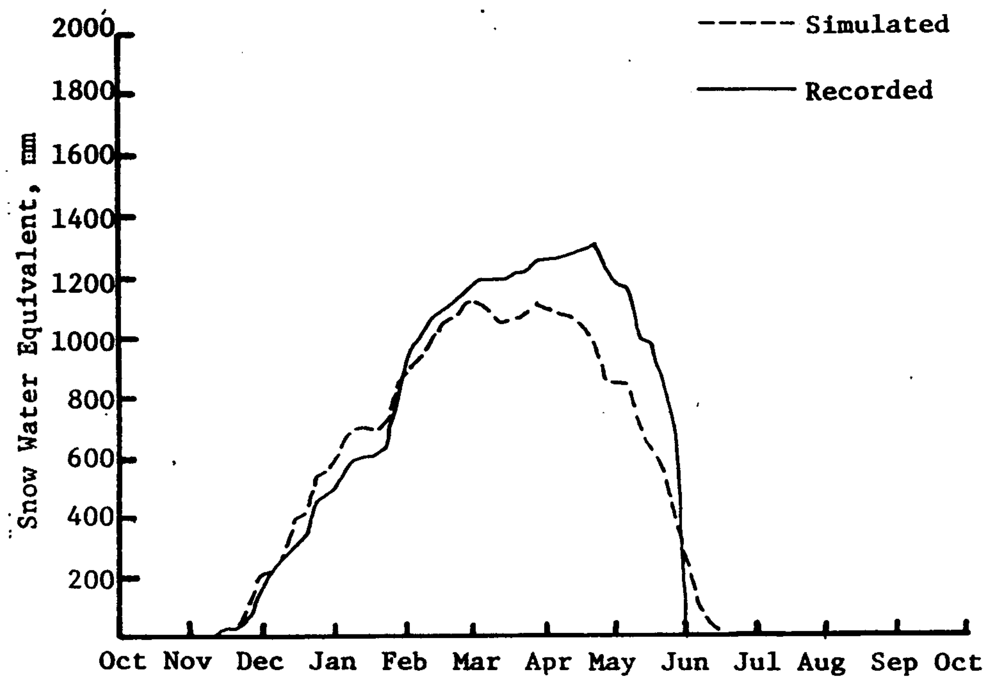

Figure 3(a). Simulated and recorded snowpack elevation zone 4, water year 1965.

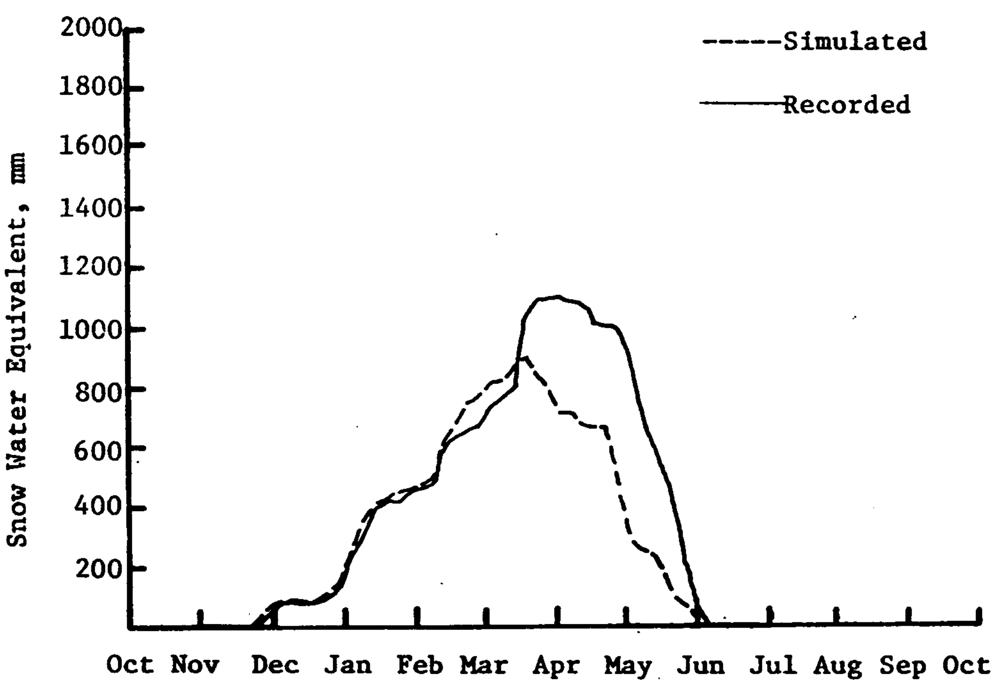

Figure 3(b). Simulated and recorded snowpack elevation zone 4, water year 1966.

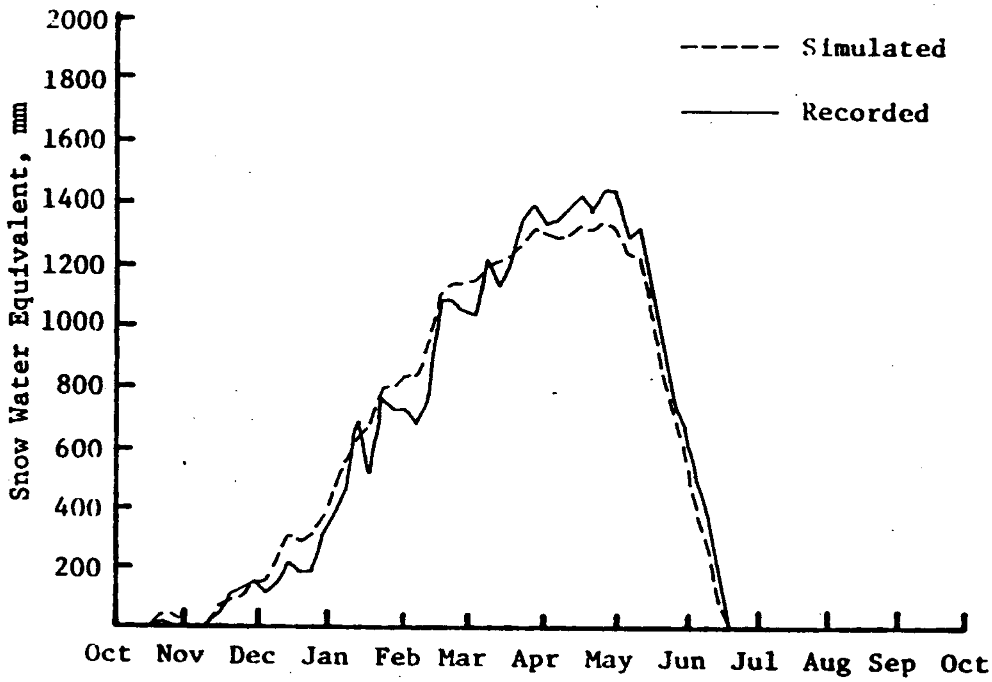

Figure 3(c). Simulated and recorded snowpack elevation zone 4, water year 1967.

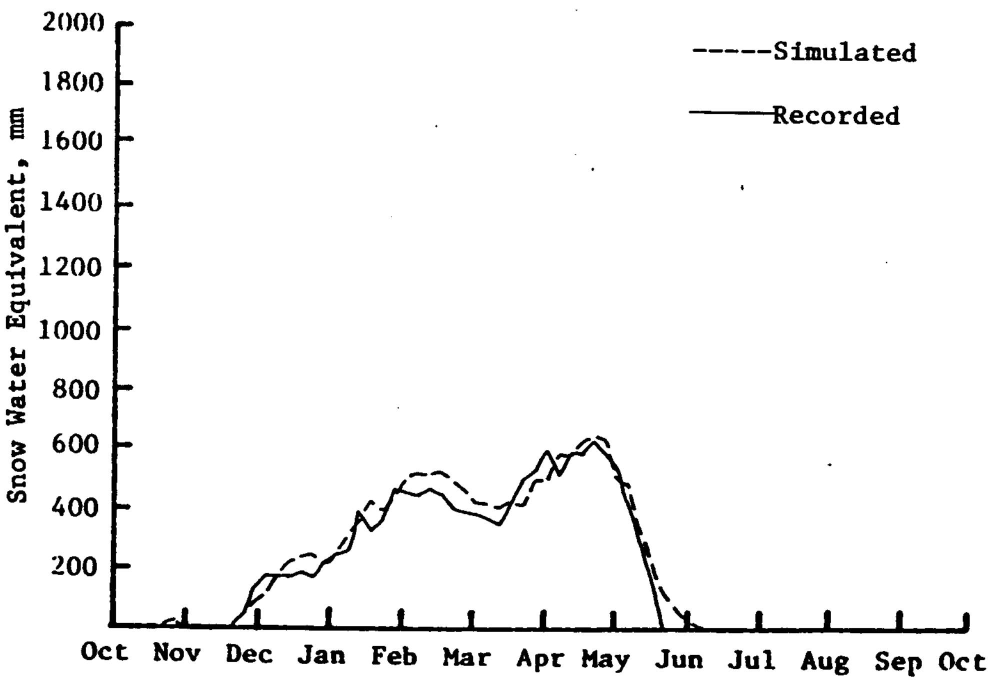

Figure 3(d). Simulated and Recorded snowpack elevation zone 4, water year 1968.

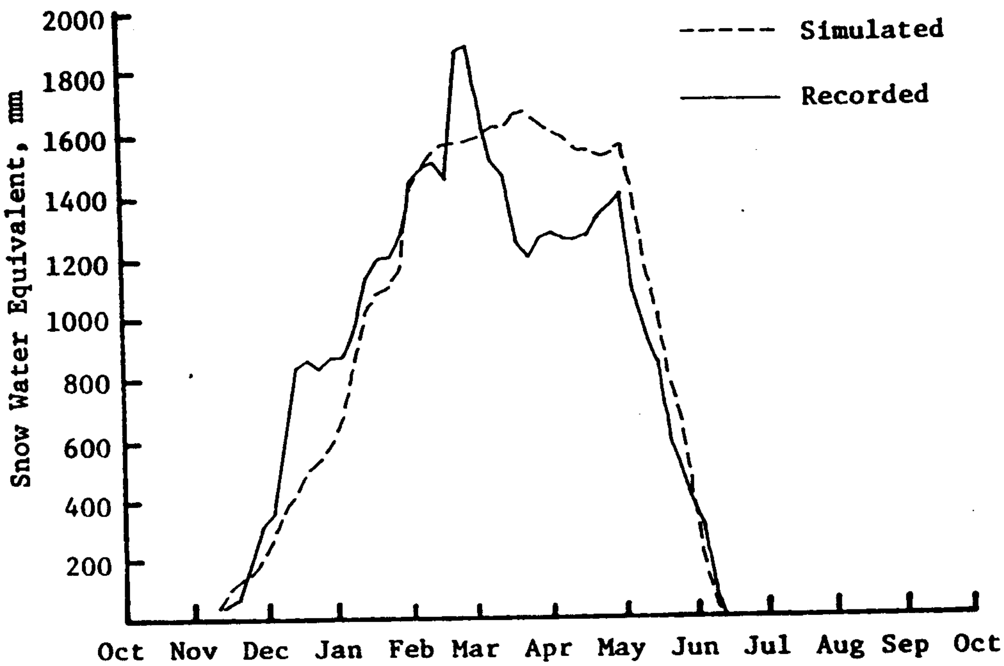

Figure 3(e). Simulated and recorded snowpack elevation zone 4, water year 1969.

insufficient to meet the objectives of the calibration process. Consequently, direct snow model calibration was attempted only for zone 4. The zone 4 model parameters were then applied uniformly for all zones.

Subsequent calibration was performed by attempting to alter parameters in the snow and runoff models in such a manner as to (visually) minimize the average calibration error on a monthly and annual basis. Initially, annual water balances were preserved by adjusting the precipitation factor in the snowmelt model. Potential evapotranspiration, also read as a model input, was estimated from observations recorded at the State Agricultural Experiment Station at Puyallup, approximately 50 mi to the SW, and adjusted on the basis of more limited data collected by the University of Washington College of Forestry in the lower Cedar River basin. Since direct measurements were not available, the monthly ET distribution was considered fixed but the magnitudes were varied in the calibration process, consistent with reasonable judgment as to watershed and climatic characteristics.

In the calibration process, it was found that 1969 appeared to be an anomolous year. Although not evident from the snow water equivalent simulations, 1969 annual runoff was greatly overestimated, while the other four calibration years tended to be underestimated (Table 3(a) and (b)). This

Table 3(a). Annual Calibration Errors, Cedar River

Water Year	Water Balance Error (inches)	Percent Error
1965	- 6.32	- 7.20
1966	- 6.73	- 9.56
1967	- 2.06	- 2.36
1968	2.73	2.77
1969	17.58	20.20
avg. error	1.04	1.20
avg. absolute error	7.08	8.20

Table 3(b). Seasonal Runoff Calibration Errors, Cedar River (April through July)

Water Year	Water Balance Error (inches)	Percent Error
1965	2.20	6.7
1966	- 7.03	-17.0
1967	1.10	3.4
1968	4.30	15.9
1969	16.51	36.5
avg. error	3.42	9.6
avg. absolute error	6.23	17.5

resulted from a substantial oversimulation of 1969 spring runoff, despite the apparently adequate calibration of the snow model (Fig. 3(e)). One possible explanation is that the winter of 1969 was a very cold one, with much greater accumulation of snow at low elevation than occurs in most years. Also, many storms during the winter of 1969 came from the interior of northern Canada, rather than from the Gulf of Alaska, and so were accompanied by northerly winds rather than southwesterlies which are more typical of storm fronts reaching the basin in normal years. This difference in storm characteristics could have had the effect of altering the deposition of snow relative to normal patterns enough to have caused a much greater buildup of snow pack over the basin than was reflected by the recorded precipitation. Another possibility is that the difference in storm types may have altered precipitation gage catch efficiency. Ideally, precipitation gage recordings would be adjusted continuously for wind velocity and direction. This is not normally possible, however, and a constant adjustment factor is used by the model. In any event, by comparison with other years in the calibration period (1965-69) and the verification period (1970-74) it appears that 1969 is in some respects anamolous.

Summary statistics for the calibration and verification periods are presented in Tables 4 and 5. Seasonal errors are for the period April 1 - July 31, the period during which most snowmelt runoff occurs for this basin. Consequently, accurate calibration during this period is critical. Comparison of Tables 4 and 5 shows that the calibration period errors are consistent with those of the verification period, indicating that at least the model has not been 'overfit' to the calibration period data. Figure 4 summarizes the mean absolute prediction errors for both the calibration and verification periods by month. From this figure, it can be seen that the bias (mean error) is strongly seasonal, but that the mean absolute error, a measure of the variability of the model error, is nearly uniform. Figures 5(a)-(f) provide graphical comparisons of simulated and recorded streamflows for the verification period. Analysis of these figures shows the importance of errors in

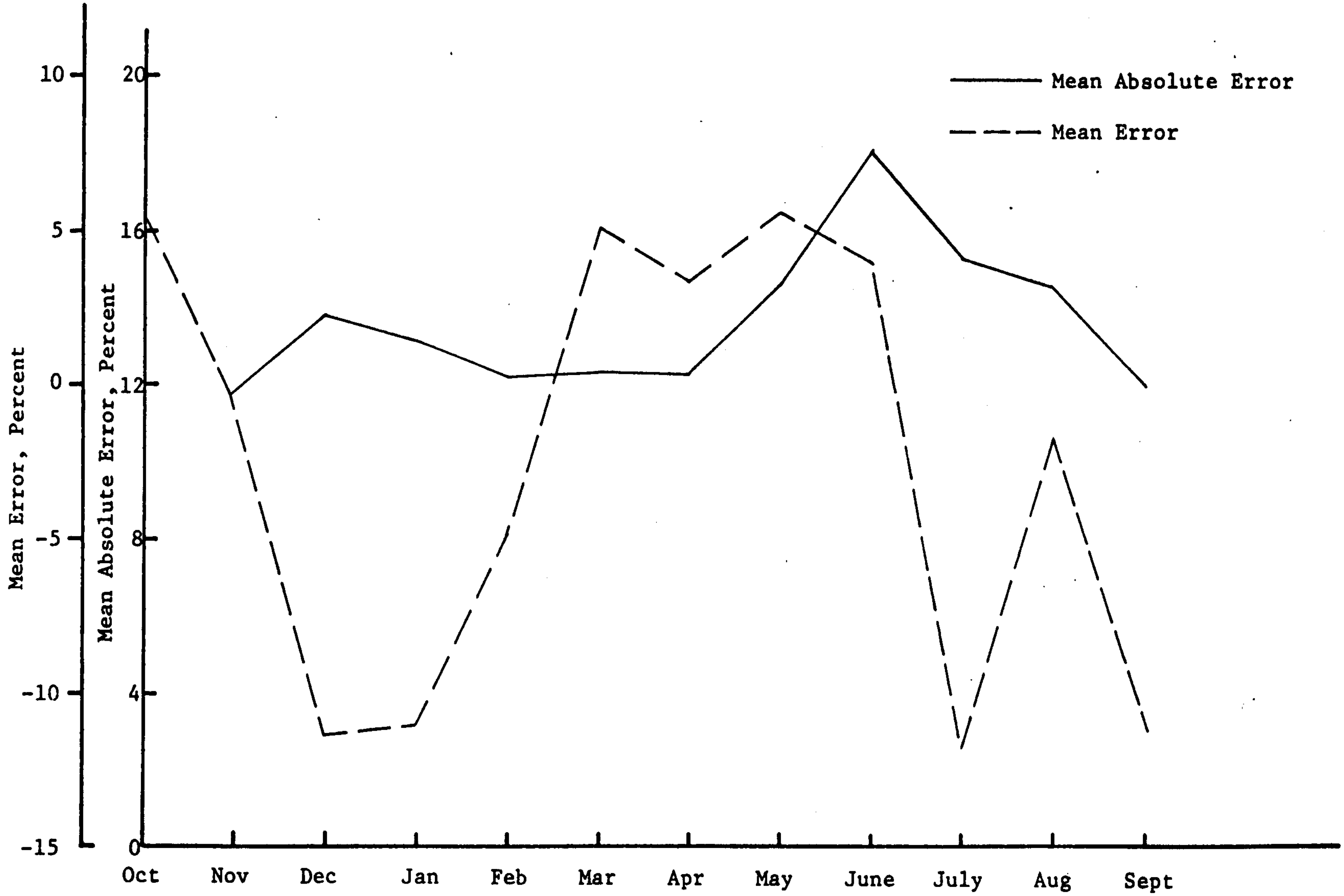

Figure 4. Seasonal Simulation error distribution for Cedar River.

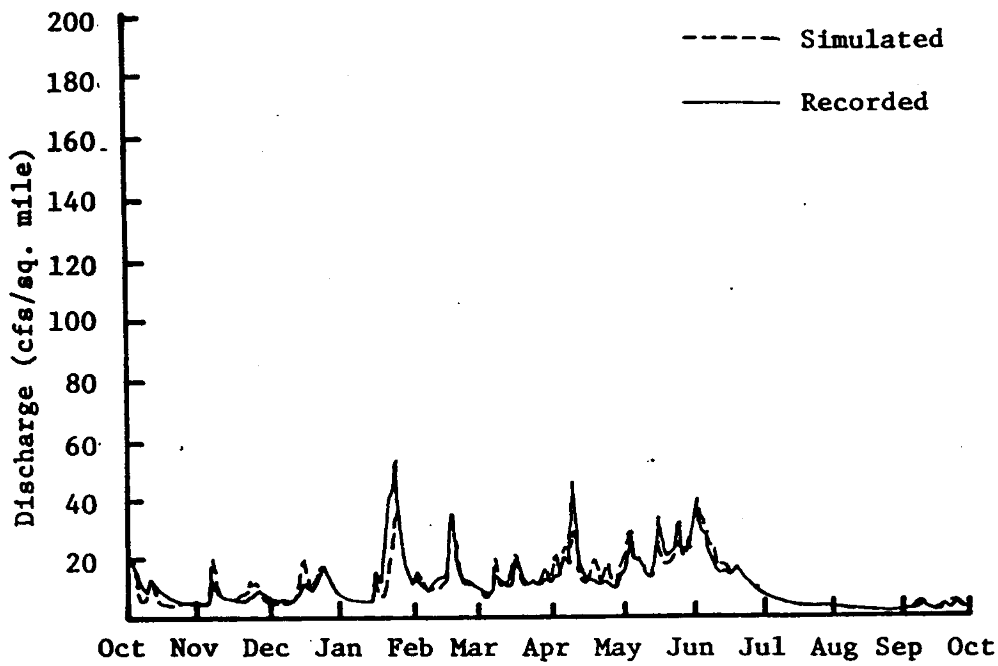

Figure 5(a). Simulated and observed runoff at U.S.G.S. station 12-1150 (Cedar River near Cedar Falls), water year 1970.

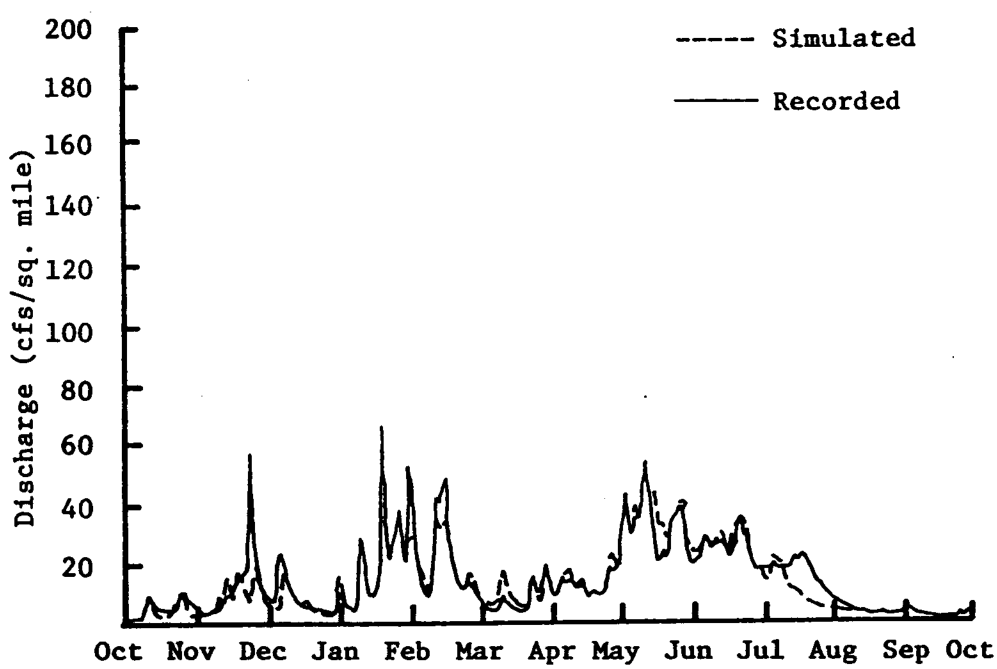

Figure 5(b). Simulated and observed runoff at U.S.G.S. station 12-1150 (Cedar River near Cedar Falls), water year 1971

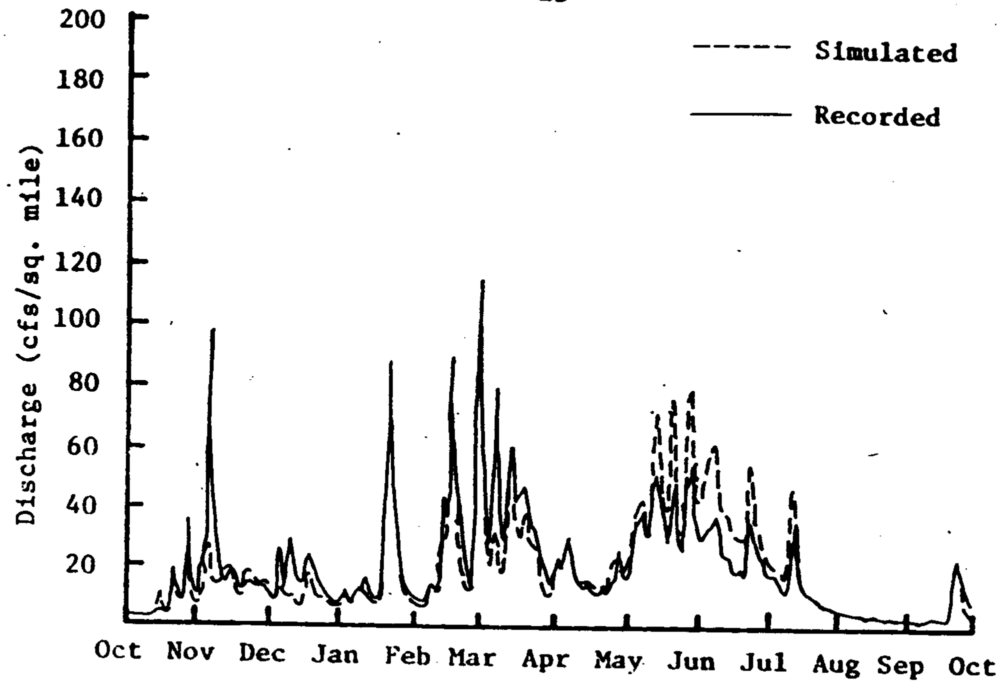

Figure 5(c). Simulated and observed runoff at U.S.G.S. station 12-1150 (Cedar River near Cedar Falls), water year 1972

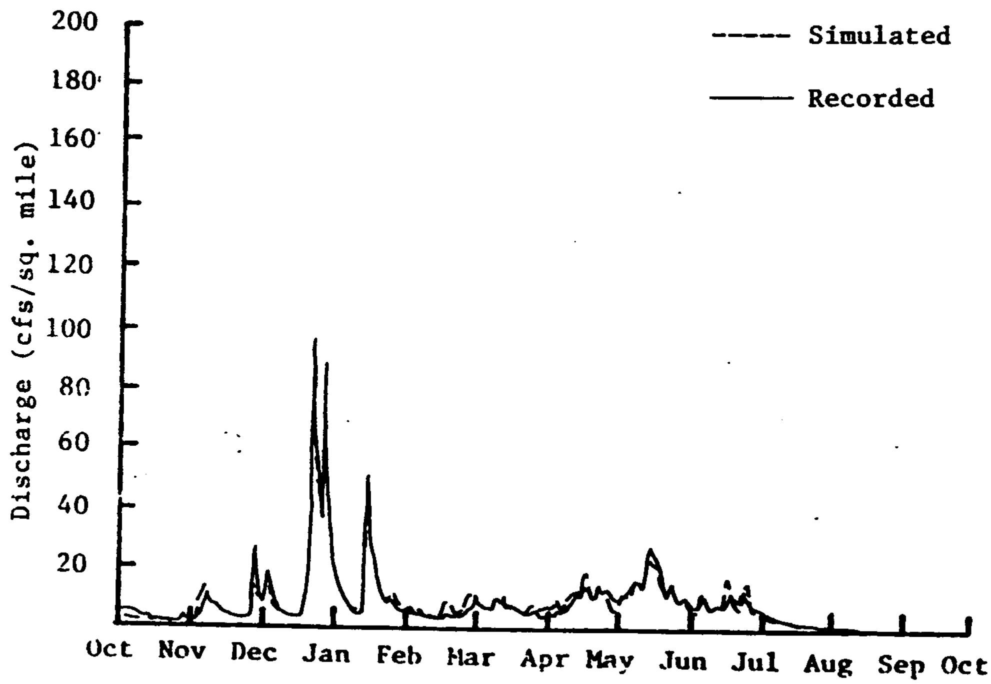

Figure 5(d). Simulated and observed runoff at U.S.G.S. station 12-1150 (Cedar River near Cedar Falls), water year 1973.

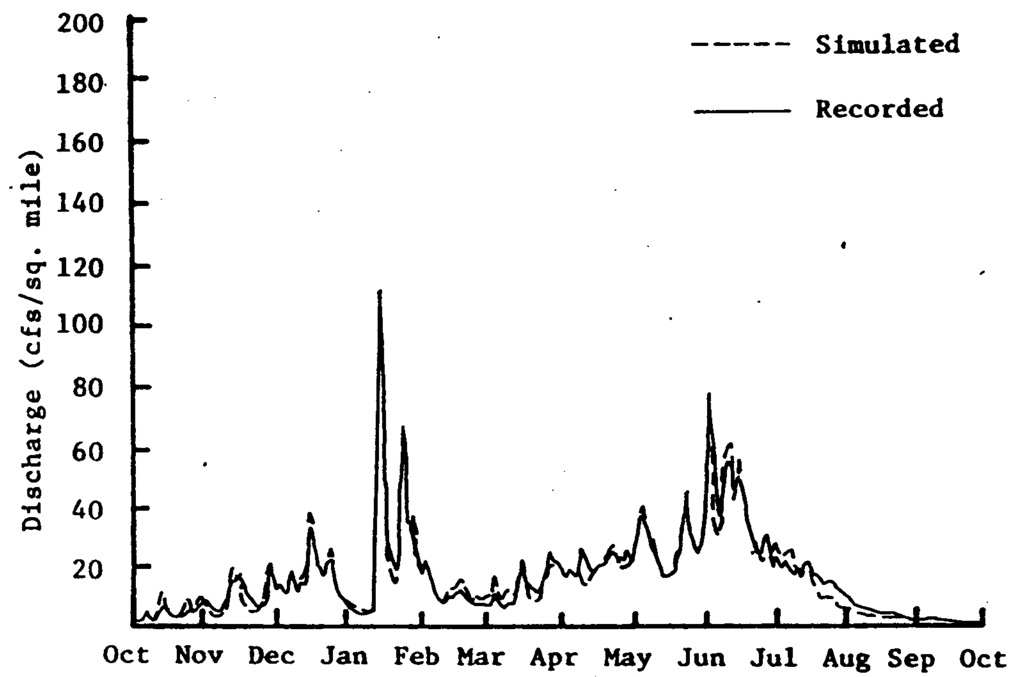

Figure 5(e). Simulated and observed runoff at U.S.G.S. station 12-1150 (Cedar River near Cedar Falls), water year 1974.

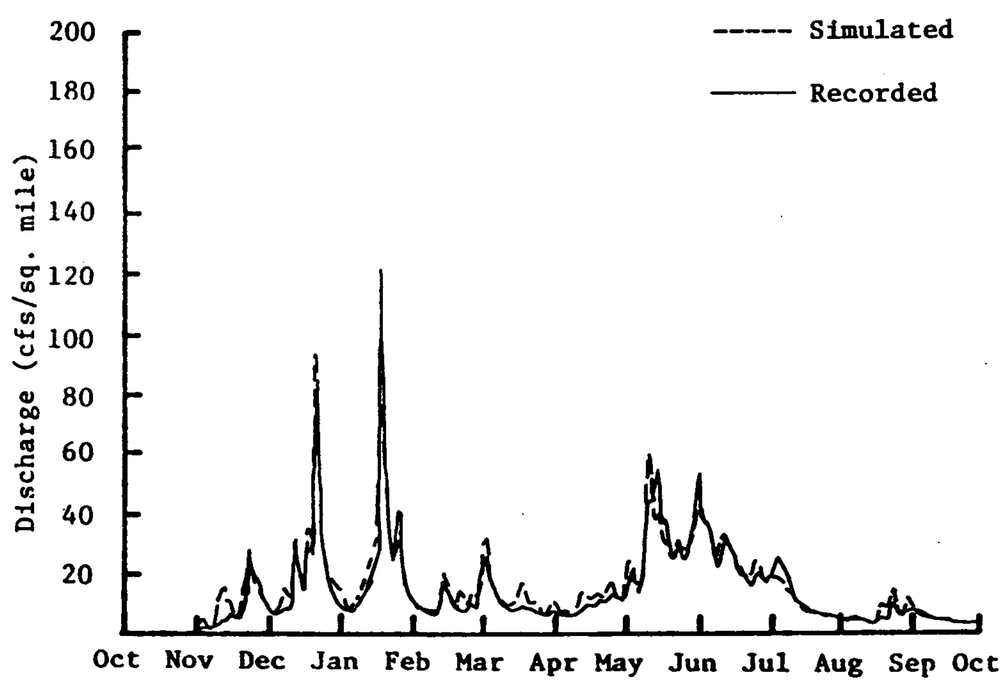

Figure 5(f). Simulated and observed runoff at U.S.G.S. station 12-1150 (Cedar River near Cedar Falls), water year 1975.

Table 4. Monthly Calibration Errors, Cedar River.

Water Year	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.
1965	22.4	0.1	-37.9	-23.1	-16.4	0.2	1.9	25.2	-1.8	-27.7	-5.7	-17.6
1966	-13.4	-2.7	-6.8	4.3	28.1	2.8	-20.4	-3.7	-29.9	-27.5	-11.7	0.0
1967	-7.1	-0.3	-13.5	-15.2	0.0	16.2	27.9	-8.7	7.4	4.1	29.2	9.4
1968	36.9	20.4	-11.8	-16.0	-13.9	22.3	22.2	18.7	14.3	-8.1	0.0	-24.4
1969	7.8	1.9	0.9	8.8	-9.7	-1.8	16.7	39.2	62.8	8.5	-8.1	5.9
mean error	14.8	4.5	-15.8	-12.0	-7.9	8.9	4.9	15.2	13.2	-10.4	-0.0	-13.6
mean absolute error	19.6	5.5	16.1	15.2	12.4	9.4	16.2	20.2	24.7	15.8	8.8	17.1

Table 5. Monthly Verification Errors, Cedar River.

Water Year	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.
1970	-16.7	22.8	8.5	-25.6	-0.9	6.3	3.8	-2.8	7.6	5.0	18.9	-4.8
1971	-15.4	-17.9	-7.5	-14.1	-10.3	29.4	13.5	7.3	8.7	-35.6	-26.6	-7.0
1972	-7.1	-26.9	-40.0	-8.2	-17.6	-23.9	7.2	32.3	55.5	21.6	10.7	-3.9
1973	-21.3	5.1	-9.1	-1.8	40.4	8.1	14.0	-5.5	3.1	-7.0	16.8	-6.7
1974	38.9	-18.2	4.3	-14.1	11.8	4.2	-6.4	-0.4	-3.3	-3.5	-32.9	-3.8
1975	13.9	37.6	15.1	15.3	21.9	31.0	29.7	-8.6	3.6	-15.2	24.8	-6.7
mean error	-5.6	-6.1	-3.6	-6.7	-2.2	-1.0	5.0	5.4	10.0	-7.3	-4.8	-4.2
mean absolute error	14.5	18.3	11.6	11.4	11.9	15.4	8.6	9.1	11.6	14.6	20.1	4.2

correctly simulating the timing of snowmelt runoff, a point which is somewhat obscured by the summary measures of Tables 4 and 5 and Figure 4. There is also an indication that in some years, early summer runoff simulation errors result from poor prediction of snow water storage, i.e., the model predicts less snow water storage (1971 July-August) or more storage (1972 June-July) than is suggested by the recorded runoff. If adequate data were available, it might be possible to correct predicted snow water storage in each elevation zone prior to the runoff season. This has not been attemped here, so the estimated forecast accuracy could potentially be improved somewhat.

Results

Estimates of forecast accuracy using the modified HM model for the Cedar River near Cedar Falls were presented by Lettenmaier (1978). In this work, forecast accuracy was estimated using a split sample method, where the first nine years of coincident streamflow, snow course, and precipitation data (beginning with water year 1949) were used to estimate model parameters, and forecasts were made for years 10-12. Subsequently, parameters were reestimated using the first 12 years of data, and forecasts were made for years 13-15. This procedure was repeated until forecasts had been obtained for the last 18 years of record. A summary index, the coefficient of prediction, C_p, was then computed as

$$C_p = 1 - \frac{MSE}{S_p^2}$$

where

$$MSE = 1/n \sum_{i=1}^{n} (R_i - \hat{R}_i)^2 ,$$

$$S_p^2 = 1/n \sum_{i=1}^{n} (R_i - 1/n \sum_{i=1}^{n} R_i)^2$$

and where R_i is recorded forecast period runoff in year i, and $\hat{R}_i$ is the (split sample) forecasted runoff.

For the HM model and its variations, the parameters are estimated statistically by minimizing prediction errors during the calibration period. Consequently, the parameter estimates become more precise as more years of data become available (each year of record is effectively one observation for parameter estimation purposes). For this reason, the variable length calibration period, or split sample technique, was used; forecasts for the most recent years of record are made using parameters whose error of estimation tends to be smaller in a statistical sense.

Estimation of forecast accuracy using the NWS models is a more difficult problem. If the same technique were used as was employed for the HM model, it would be necessary to recalibrate the model every three years. However, it is generally recognized that so long as the calibration period includes a moderately wet and a moderately dry year, little improvement in parameter estimation is obtained by using a calibration period longer than four or five years. Also, parameter estimation is not automated for these models (although an optimization algorithm may be employed to assist in parameter estimation as discussed in Chapter 3), so recalibration would be a tedious undertaking, with no apparent benefit.

Another problem in estimation of forecast accuracy using the NWS models is that forecasts are obtained by performing a simulation, using recorded data through the forecast date and so-called alternate scenario rainfall data during the forecast period. Typically, three scenarios are used, with a high, moderate, or 'average' and low precipitation sequence selected from the historic record. The model is then run sequentially for each such sequence. To obtain forecasts for many years, one ideally would make hypothetical forecasts for, say, the i'th year, then rerun the model using the recorded precipitation for year i in making a forecast for year i + 1, and so on. This poses logistical problems, and greatly increases the computational expense. In this work, we simply compiled three long precipitation records containing historic data for all except the forecast period, during which rainfall data for the high, average, and low scenarios were inserted. Insofar as water years are the basic time unit, this appeared to result in minimal differential carryover effects since the model storage zones are usually nearly empty at the beginning of the water year. Some small differences in forecasts might result in years during which the actual forecast period precipitation is extreme if a different approach were used.

Another complication is that the calibration period (1965-69) is within the period used to estimate forecast accuracy. Ideally, a separate calibration period would be used. However, this was not possible since snow water equivalent measurements at Stampede Pass, used in the calibration, were not taken before 1965. However, simulation errors during the calibration and verification periods (Tables 4 and 5) are consistent; there is no evidence of overfitting. For this reason, inclusion of the calibration period within the period used for estimation of forecast accuracy was considered unlikely to bias the analysis.

One final problem in performing an assessment of forecast accuracy for the NWS model is that, since alternate precipitation scenarios are selected from the same period of record used in the analysis, an alternate precipitation sequence must be selected when making a forecast for the year(s) from which the original scenarios were drawn. Consequently, a primary (used in all years except that from which it was drawn) and a supplementary (used in one year only) precipitation sequence for high, average, and low conditions must be selected. Forecasts for the Cedar River runoff were made for the period April 1 - July 31. Selection of data sequences to be used in the forecast period was performed by summing the forecast period precipitation at Stampede Pass and Cedar Lake, and expressing each total as a fraction of the average for the period. The moderate sequences chosen were those which had forecast period precipitation closest to 100% of average. Extreme years were selected by finding the closest extreme pair having nearly the same total precipitation (not necessarily a given percentile). The sequences selected are given in Table 6.

Table 6. Primary and Supplementary Precipitation Sequences Used in Cedar River Forecasts

Scenario		Year	Runoff Inches	Per Cent of Average
Low	primary	1958	30.24	79.3
	supplementary	1957	31.15	81.7
Moderate	primary	1961	38.08	99.9
	supplementary	1963	38.01	99.7
High	primary	1972	50.23	131.7
	supplementary	1964	49.35	129.4

The results of the simulations are reported in Table 7. For each year, the observed April 1 - July 31 runoff is given, along with the forecasted run-off using the high, moderate, and low precipitation sequences. The simulated runoff is that predicted by the model using the recorded precipitation, hence this corresponds to a perfect forecast of precipitation and reflects model error only.

Examination of the results shows that the actual runoff often falls outside the envelope of the high and low simulations. This indicates that the dominant source of forecast error is error in the model simulation of winter conditions, significantly errors in accurately estimating areal precipitation. Differences in estimation of

Table 7. Cedar River April 1 - July 31 Forecast Results[a]

Year	Observed	High	Average	Low	Simulated
1956	62.48	62.75	58.49	56.53	-
1957	36.24	41.27	37.55	34.84	-
1958	27.81	34.92	31.31	26.57	-
1959	40.38	44.79	40.81	38.37	-
1960	35.75	39.42	35.81	33.01	-
1961	35.01	44.80	37.22	38.46	-
1962	31.61	40.01	36.30	33.61	-
1963	22.17	29.68	26.36	23.34	-
1964	58.43	55.78	51.70	49.54	53.02
1965	32.62	46.32	42.47	39.81	34.70
1966	41.24	39.94	36.36	33.46	34.24
1967	31.97	46.33	42.18	40.09	33.07
1968	27.00	30.16	26.80	23.89	31.30
1969	45.25	63.85	59.59	57.99	61.76
1970	33.23	37.43	33.68	30.98	34.10
1971	51.15	59.64	55.43	53.57	51.04
1972	50.81	62.68	63.19	61.55	67.39
1973	22.59	29.17	25.97	22.95	22.90
1974	62.00	61.34	57.11	55.37	60.04
1975	42.32	50.06	46.04	43.58	41.64

[a] units are inches over watershed

forecast period precipitation have a smaller effect in contributing to forecast error for an April 1 forecast, since most of the subsequent runoff is already in storage in the basin in the form of snow or subsurface moisture, and the forecast problem is effectively one of estimating the amount stored. For forecasts earlier in the spring, forecast period precipitation variability will play a more significant role in contributing to forecast error.

For comparison purposes, the measure used is the coefficient of prediction defined earlier in this chapter. This index, when computed from the data of Table 7, is approximately 0.72, which compares with a value of 0.76 for the modified HM model (Lettenmaier and Garen, 1979). In light of the differences in methods of estimating forecast accuracy for the two models, it is doubtful that the difference in the C_p values is statistically significant.

There remains a question as to whether one model might be persistently more accurate under certain conditions, for instance, extreme low flow. This question is deferred to Chapter 4, where it can be addressed in light of results for both the Cedar and Cispus Rivers.

Chapter 3

CASE STUDY 2: CISPUS RIVER

The second watershed modeled was the Cispus River above USGS gage #14-2325 near Randle, Washington. The Cispus is a major tributary of the Cowlitz River, with a drainage area of 321 mi^2. It is important in providing a major portion of the inflow to two reservoirs owned by Tacoma City Light, which are used primarily for hydroelectric power generation with secondary use for flood control and recreation, as well as fisheries protection. Like the Cedar, the Cispus is a westward draining stream with headwaters on the crest of the Cascade mountains. The elevation of the basin ranges from 1221 ft at the gage to 12,300 feet at the peak of Mt. Adams, a volcano whose elevation is the second highest in the State of Washington. That part of Mt. Adams lying within the Cispus River basin includes a small glaciated area (less than 2 mi^2) which has an insignificant effect in the present study but which does play a role in maintaining base flow during the late summer months.

The Cispus River provides a more difficult modeling problem than does the Cedar because of a lack of data. There are no meteorological stations within the basin, nor are there any snow courses with sufficient record to be useful for calibration purposes. There are several stations within 60 mi of the basin centroid, however, most of these are at low elevation and none provide hourly records. The only high elevation meteorological data in the vicinity of the watershed are collected at two stations on Mt. Rainier, approximately 45 mi from the basin centroid. Although the basin is much larger than the Cedar River basin and has a much greater elevation range, none of its tributaries are gaged, so the only calibration point is the primary gage. Although these problems increase the difficulty of implementing conceptual models such as the NWS models used here, this basin is perhaps more typical with respect to size and data availability than the Cedar, so model accuracy results should be of considerable practical interest.

It is worth noting that the HM model is not so restricted by data availability as are conceptual models, so the Cispus basin provides an interesting test of this model as well. It is often the case that the precipitation stations providing the best forecasts when the HM model is used do not lie within the basin. Likewise, large basins do not necessarily result in degraded performance; Lettenmaier and Garen (1979) found that HM model performance was apparently only minimally affected by drainage area for basins ranging in size from 41 mi^2 (the Cedar River, as discussed in Chapter 2) to over 2000 mi^2 for several tributaries of the Salt River in Arizona.

Model Implementation

As in Chapter 2, most emphasis here is placed on implementation of the NWS models because of their greater complexity. However, results for the modified HM model as applied to the Cispus River have not been reported elsewhere, so a brief discussion of application of this model is in order.

The HM model is self-calibrating, so user judgement enters only into the choice of test season length (Tangborn, 1979) and selection of precipitation stations. The latter can also be automated through use of a screening model as described by Lettenmaier (1978). Tangborn (personal communication, 1980) has found that for forecasts of the Cowlitz River at USGS gage #14-2324 (downstream of the confluence of the Cispus and Cowlitz Rivers) the rainfall record at Kid Valley (NWS 45-4201) provides the best forecasts.

As a check, the screening model mentioned above was used for selection of precipitation stations where the candidates were Kid Valley, Rainier Ohanapecosh (NWS 45-6896) and Rainier Longmire (45-6894). Kid Valley performed substantially better than the other two and was used in obtaining the HM model results described later in this chapter.

Three snow courses were identified which had a sufficient data record and were close enough to the basin (none actually lie within the basin) to be potentially useful in performing forecasts using the modified HM model. These are Cayuse Pass (Soil Conservation Service 21C6), Plains of Abraham (22C1A), and Surprise Lakes (21C13a). The screening model selected the Plains of Abraham as the best predictor for all forecast seasons tested.

Implementation of the NWS model was a more difficult task because of the sparseness of meteorological data. High elevation precipitation data are available for several stations in the vicinity of Mt. Rainier, approximately 40 mi to the north of the basin. Although these data were used in the absence of better stations, spatial variability of mountain precipitation is such that the data are somewhat suspect, since they do not lie within the basin. Although gages lying outside the forecasted basin are routinely used in the HM model, the data requirements of the HM and NWS models are fundamentally different; whereas the HM model requires only seasonal aggregate precipitation and forecasts seasonal runoff directly, the NWS (and other conceptual models) operates at a subdaily time scale and attempts to simulate runoff on a daily time scale. Forecasts are made by aggregating runoff predictions (daily) to obtain seasonal totals. Consequently, it is important that the precipitation data used accurately reflect the temporal and spatial distribution of storms occuring in the basin, and stations which lie within the basin or very close to its boundaries are favored. In this case, however, and for many other mountainous watersheds as well, there is little choice in station selection and several stations relatively remote from the basin had to be used. The data stations which were selected are shown, along with the basin boundaries, in Fig. 6.

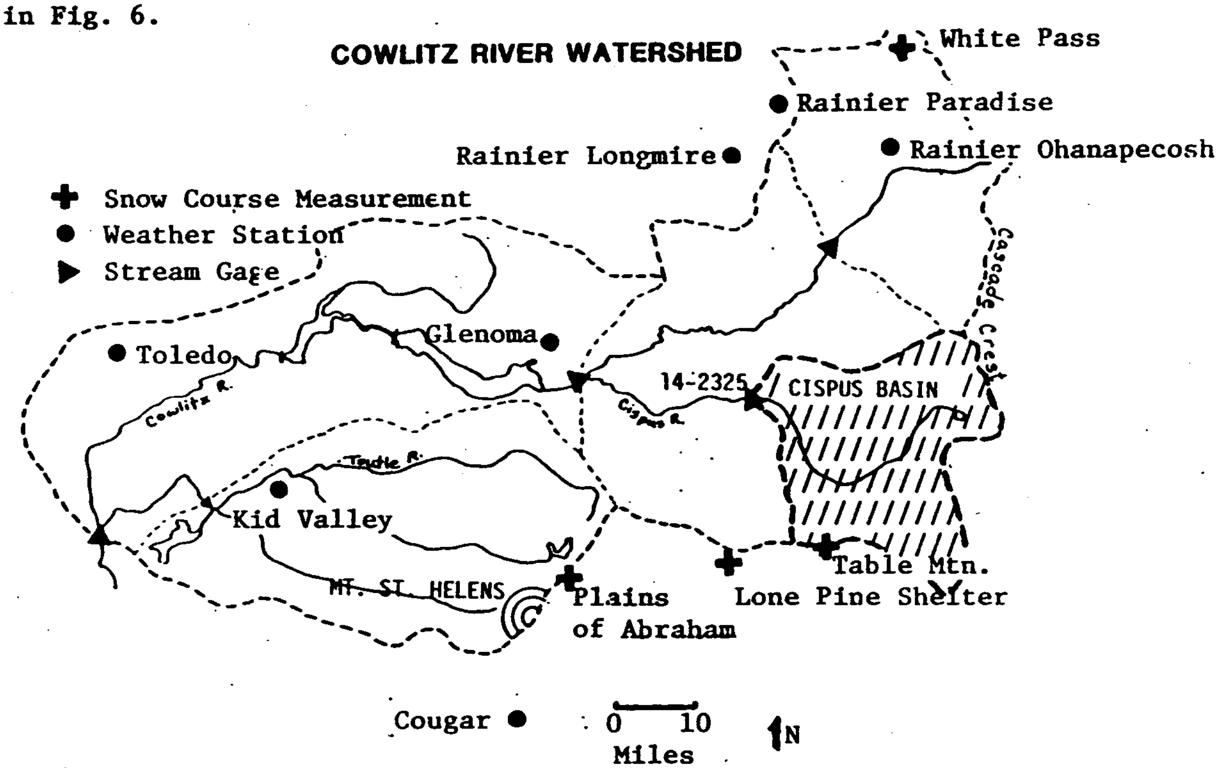

Figure 6. Cowlitz and Cispus River Watersheds with data stations.

Because of the influence of local geography on mean precipitation accumulations in mountainous watersheds (see Lettenmaier, et al., 1981 for an extreme example) it is necessary to rescale precipitation at the various sites to obtain magnitudes which are representative areal averages, as opposed to point accumulations. In considering the wide range in elevation within the basin, it was decided to use five elevation zones. As for the Cedar River, these zones do not represent physical subbasins, but are merely a mechanism for modeling differences in snow accumulation with elevation. The data range represented by each zone, and the fraction of watershed area associated with each are shown in Table 8. Ideally, these zones would each represent about equal fractions of the watershed area. However, the work reported here was carried out simultaneously with a study of the impact of the May 18, 1980 eruption of Mt. St. Helens on flood hazards in several subbasins of the Cowlitz River, including the Cispus. Some compromises were effected to reduce the logistical requirements associated with data preparation, and the somewhat unequal apportionment of area by zones reflects this.

Table 8. Cispus River Basin Elevation Zones

Zone	Percent of Watershed Area	Midpoint Elevation, ft
1	5	1500
2	25	2835
3	41	4065
4	25	5135
5	4	7900

Once the midpoint elevations of each of the zones were identified, the precipitation records used for each zone (Table 9) were rescaled to give a linear variation of annual precipitation with elevation. Although the actual

Table 9. Cispus River Basin Precipitation Stations

Zone	Precipitation Station	Station Elevation
1	Kid Valley	690
2	Rainier Ohanapecosh	1930
3	Rainier Longmire	2760
4	Rainier Longmire	2760
5	Rainier Paradise	5500

variation of areal average precipitation with elevation is not necessarily linear (in fact, meteorological considerations dictate that the rate of increase of precipitation with elevation for frontal storms should decrease with elevation) a linear variation is a reasonable first approximateion. This was achieved by initially applying a uniform scale factor to the raw precipitation record representing zone 1 (here a factor of 1.1 was used, as the midpoint of elevation zone 1 is somewhat higher than the data collection site) then estimating the annual average precipitation for elevation zone 1, as well as the annual averages of the raw records used to represent each of zones 2-5. The records for these zones were then adjusted to have the same annual average precipitation as zone 1, and subsequently scaled by an elevation zone factor α_i defined as

$$\alpha_i = 1 + \frac{E_i - E_1}{1000} \times \beta$$

where E_i is the elevation of zone i in feet, and where initially $\beta = 0.2$. This relationship defines the linear variation of precipitation with elevation. An additional precipitation adjustment factor in the snowmelt model allowed calibration to obtain a proper annual water balance. By varying this factor for the different elevation zones, it is possible to induce a nonlinear precipitation/elevation relationship with less effort than would be required to recompute the base records. However, we found that for the Cispus basin no noticeable improvement in model performance was obtained by allowing the adjustment factor to vary, so a linear relationship was maintained.

None of the precipitation stations used provide hourly data records, so the daily totals had to be divided into four six-hour increments per day as required by the snowmelt model. Unfortunately, no other stations in the vicinity of the basin have adequate (i.e., minimum missing data) hourly records for the period of record (1950-78) investigated. The nearest station with hourly data is the National Weather Service observation station at Olympia, approximately 50 mi NW of the basin.

For large storms, the subdaily distribution of precipitation tends to be relatively constant, when storm mean velocity is accounted for, over the storm area. For smaller storms, this is not likely to be the case, but for such storms the method of disaggregating the daily total will have relatively less effect on predicted runoff. Recognizing this, the method of disaggregation adopted was as follows. Initially, daily total precipitation for Olympia was classified into 4 seasons (January - March, April - June, July - September, October - December) and 3 daily totals (0 - 0.5 inches, 0.5 - 1.0 inches, and greater than 1.0 inches) for a ten year subset of the 29 year period of record. For each daily total so classified the fraction of the total occuring during each six hour period was computed, indexed, and stored. For each date on which rainfall occured for a given Cispus River zone, the ratio of the daily amount to the Olympia daily total was computed. If this ratio was less than a set value (e.g., 2.0, reflecting the occurence of a similar magnitude event at both stations) the daily total was disaggregated in the same fractions as occured at Olympia. Otherwise, the total was disaggregated in the same fraction as one of the historic Olympia storms analyzed as described above, where the specific storm was selected at random (with substitution) from all storms of the given intensity and season class. Although this method is not entirely satisfying, it does allow reasonable disaggregated totals to be computed. Also, since the runoff model accepts rainfall and snowmelt totals on a daily, rather than a six hour basis, the method of disaggregation has no effect except during periods of snowfall and/or when snow is present; otherwise, the six hour quantities are simply aggregated to daily totals.

Temperatures for each elevation zone were estimated by linear interpolation between the records for Glenoma (elevation 870 ft), Longmire (2760 ft) and Paradise (5550 ft). Insofar as spatial variability of temperature is much less than that of precipitation, the location of these stations is not as critical. However, some local biases can occur, and these may be addressed by adjusting the effective elevation of the precipitation stations relative to the zone elevation in the snowmelt program during calibration (nominally the elevation of these is identical, since temperature is estimated for the zone midpoint independent of elevation).

Snow course data suitable for model calibration were available much less frequently than was the case for the Cedar River, and it quickly became apparent that the snow course observations did not provide reasonable approximations of the average conditions over any of the elevation zones. Consequently, the snow course observations were used only to calibrate the snowmelt model to obtain reasonable dates of maximum snow accumulation. Subsequently, precipitation factors were adjusted to obtain approximately unbiased annual flow volumes. Temperature adjustments were also made to calibrate winter and spring runoff volumes. By trial and error, a uniform precipitation adjustment factor of 0.87 (model precipitation = actual precipiation *0.87) was found to be adequate. The resulting predicted annual flows and percent errors are given in Table 10 for the period 1968 - 1976 which included the calibration period 1973 - 1976 and verification period 1968 - 1972. Monthly runoff volumes for the calibration period were then examined and runoff model parameters, particularly the subsurface storage zone volumes and recession constants, were adjusted to achieve an acceptable calibration for monthly volumes. Snowmelt model parameters were then readjusted to obtain the best possible agreement on a monthly basis between predicted and recorded flows for the calibration period. Once this was done, the snowmelt model parameters were fixed and further calibration was conducted on the runoff model only.

Table 10. Annual Flow Comparisons for Cispus River

Water Year	Observed	Simulated	Per Cent Error
1968	57.56	73.81	28
1969	63.04	67.47	7
1970	53.15	54.81	3
1971	72.56	75.91	5
1972	83.09	94.90	14
1973	42.59	42.52	0
1974	88.83	81.53	- 8
1975	60.49	59.03	- 2
1976	68.62	82.32	20

Final calibration of the runoff model was achieved using an automated parameter optimization algorithm contained in the NWS runoff model, which makes use of a repetitive search to minimize an objective function consisting of a log-linear combination of three terms, including an index of mean absolute deviations of peak daily simulated and recorded flows, and similar indices of mean absolute deviations of monthly and annual simulated and recorded flows. For forecasting purposes, the accuracy of simulated peak flows is unimportant as compared with seasonal flow volumes, so this factor was removed. The optimization algorithm was then run until the objective function showed an acceptably small incremental change.

Table 11 shows the resulting errors by month for the combined calibration and verification period. Unfortunately, certain months show a persistent bias, such as April, which is included in the forecast period. Also, errors for some months are quite large, probably reflecting improper representation of precipitation in one or more of the elevation zones in certain years. This is unavoidable, in the absence of additional precipitation gages. One modification in the calibration procedure which might help and should be pursued in future work is to change the objective function in the parameter optimization

Table 11. Monthly Simulation Errors for Cispus River (percent)

Water Year	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	April	May	June	July	Aug.	Sept.
1968	128	78	33	-10	14	24	50	26	17	-8	0	46
1969	48	19	15	-25	-13	1	31	26	-12	-11	-25	18
1970	39	38	-2	-24	-6	15	21	7	11	5	-17	-17
1971	44	8	-34	-45	-12	0	25	61	0	-5	-12	-7
1972	-19	-8	-35	-74	-60	-47	12	78	85	66	24	58
1973	18	28	9	-15	28	7	13	-2	-14	-24	-43	-47
1974	19	-38	-41	-31	-13	-31	17	4	27	-7	-17	-35
1975	-36	-10	-26	-39	-22	-29	25	25	18	11	19	12
1976	49	11	-2	-15	25	-3	18	44	41	47	42	5
mean error	32	14	-9	-31	-7	-7	24	30	21	8	-3	4
mean absolute error	44	26	22	31	21	17	24	30	27	21	22	28

algorithm to incorporate a seasonal error index for the forecast period. Rather than pursuing this here, however, we elected to correct the forecasts for bias after the fact using a method described in the following section.

Figures 7(a)-(e) and 8(a)-(e) show time series plots of selected years of the calibration and verification periods, respectively, which give a general idea of the quality of simulations obtained. Persistent biases in the spring months (oversimulation) are apparent. Not apparent due to the scale used are biases in late summer and early fall months (undersimulation). Generally, error levels are higher than for the Cedar River application, which is to be expected given differences in the quality of data.

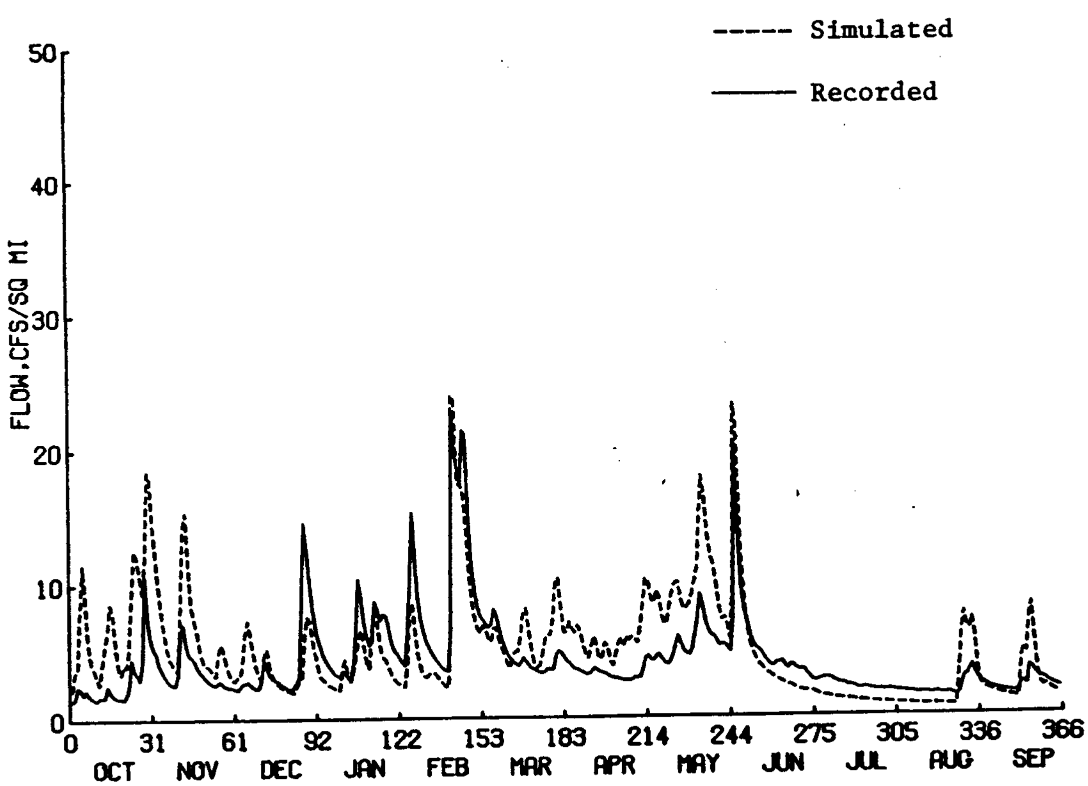

Figure 7(a). Simulated and observed runoff at U.S.G.S. station 14-2325 (Cispus River near Randle), water year 1968.

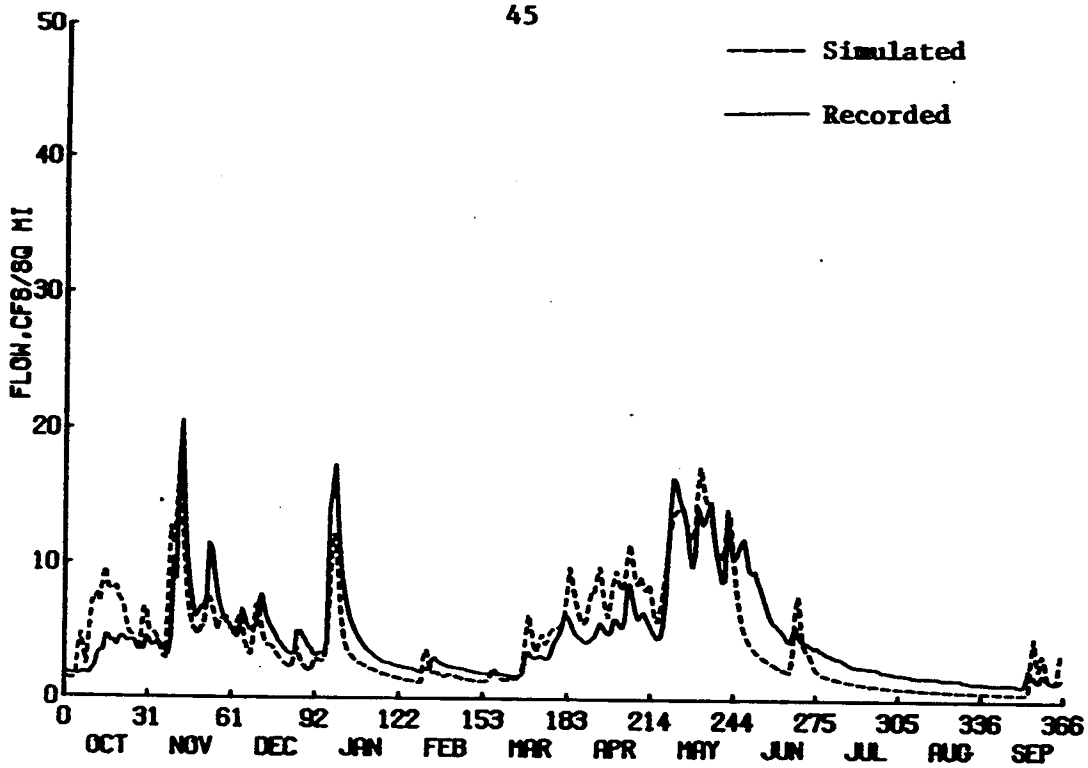

Figure 4(b). Simulated and observed runoff at U.S.G.S. station 14-2325 (Cispus River near Randle), water year 1969.

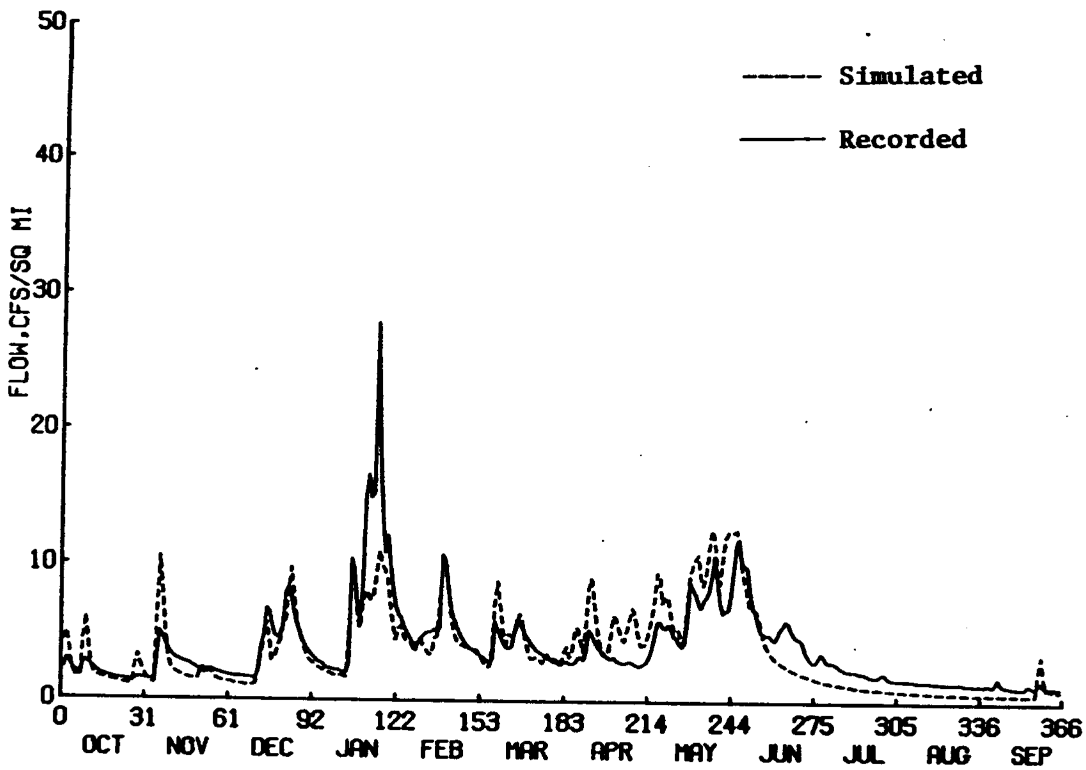

Figure 7(c). Simulated and observed runoff at U.S.G.S. station 14-2325 (Cispus River near Randle), water year 1970.

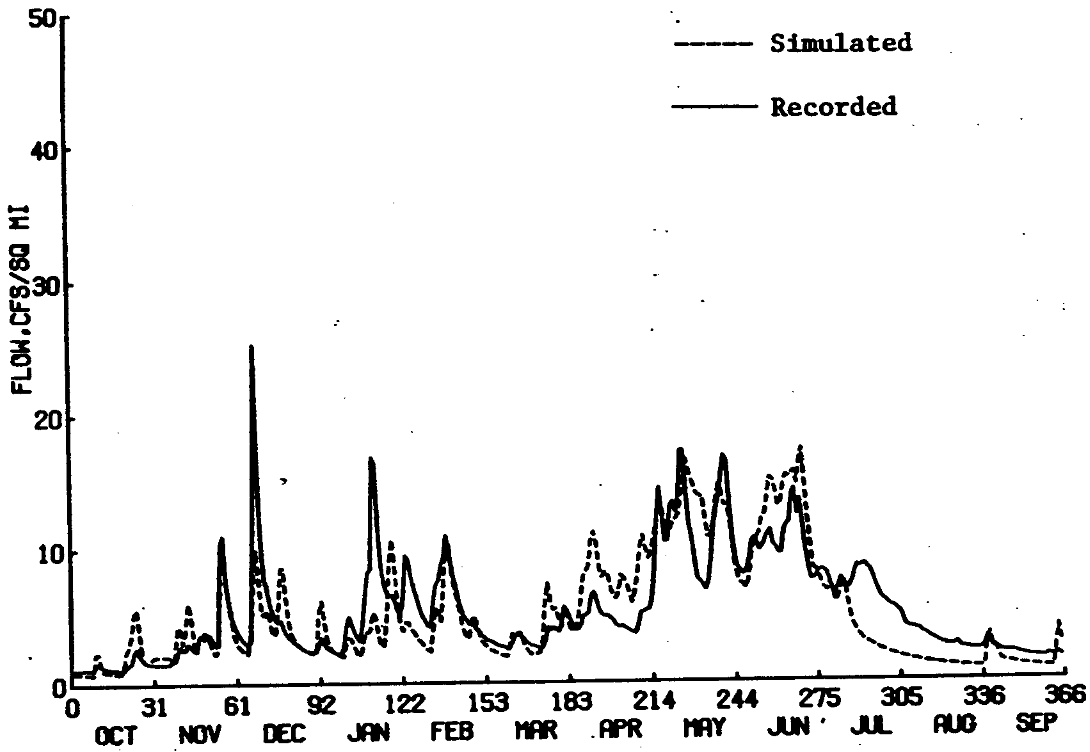

Figure 7(d). Simulated and observed runoff at U.S.G.S. station 14-2325 (Cispus River near Randle), water year 1971.

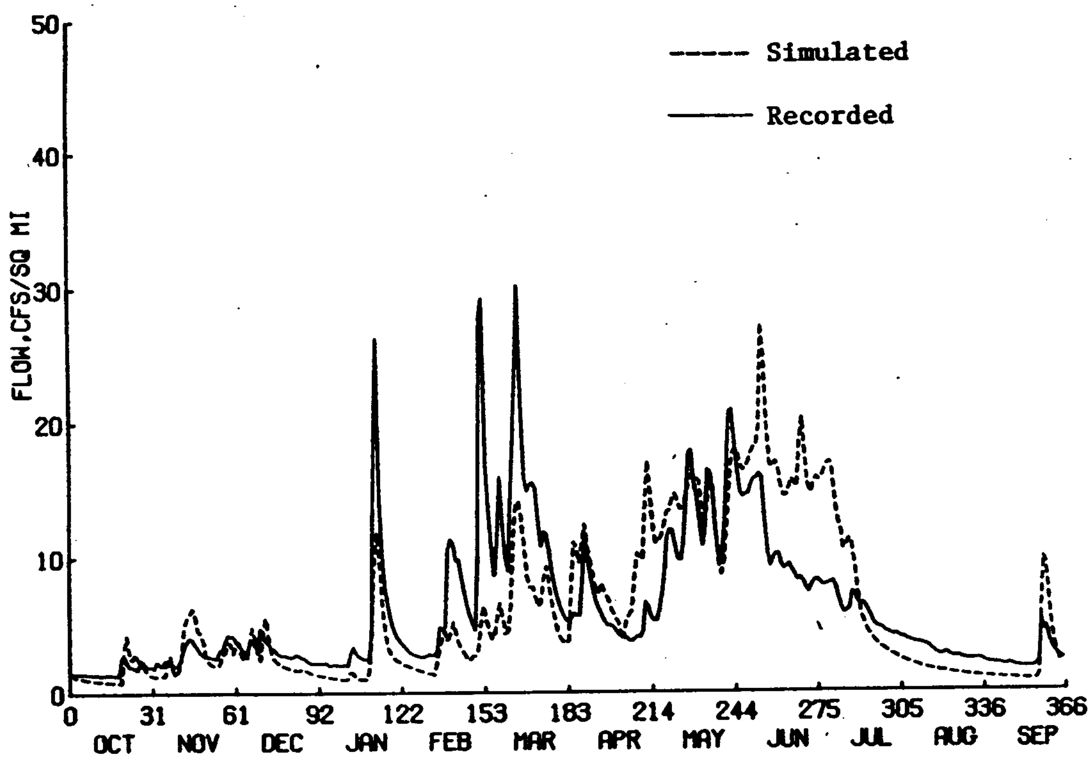

Figure 7(e). Simulated and observed runoff at U.S.G.S. station 14-2325 (Cispus River near Rnadle), water year 1972.

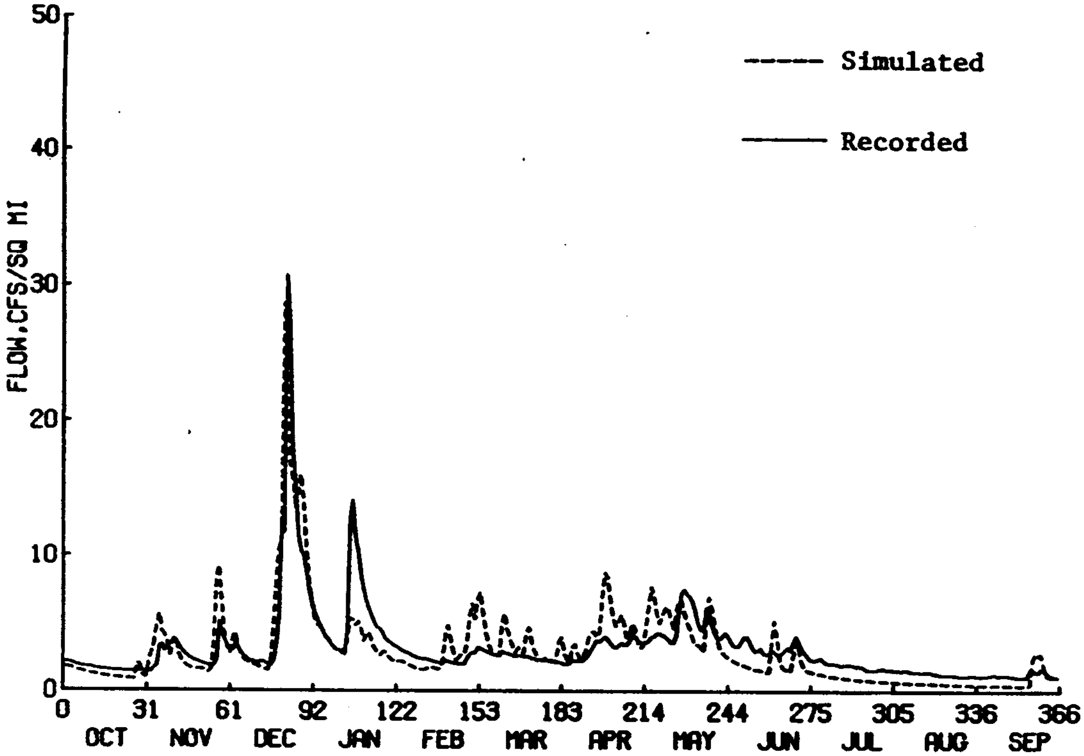

Figure 8(a). Simulated and observed runoff at U.S.G.S. station 14-2325 (Cispus River near Randle), water year 1973.

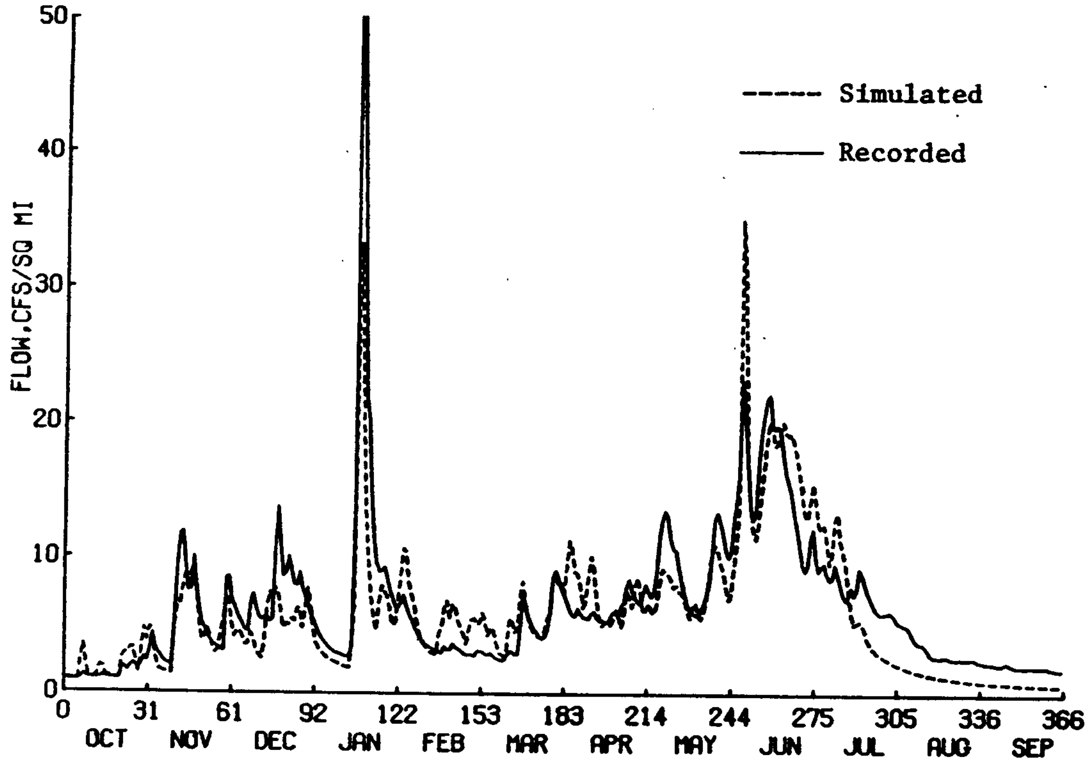

Figure 8(b). Simulated and observed runoff at U.S.G.S. station 14-2325 (Cispus River near Randle), water year 1974.

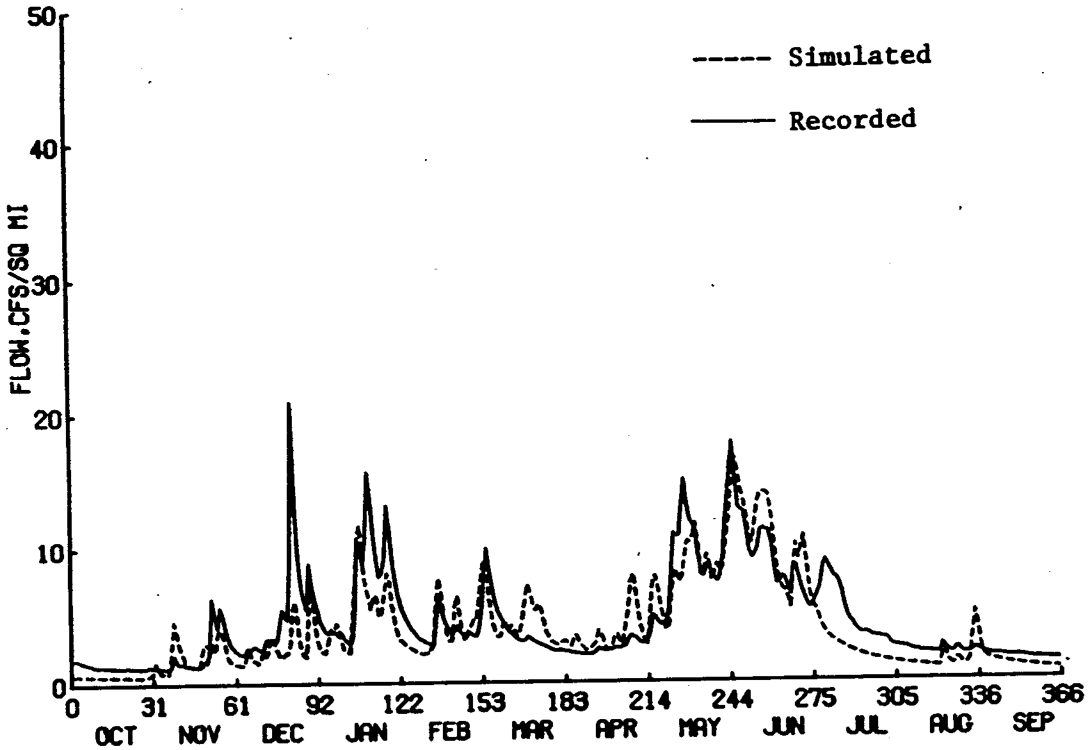

Figure 8(c). Simulated and observed runoff at U.S.G.S. station 14-2325 (Cispus River near Randle), water year 1975.

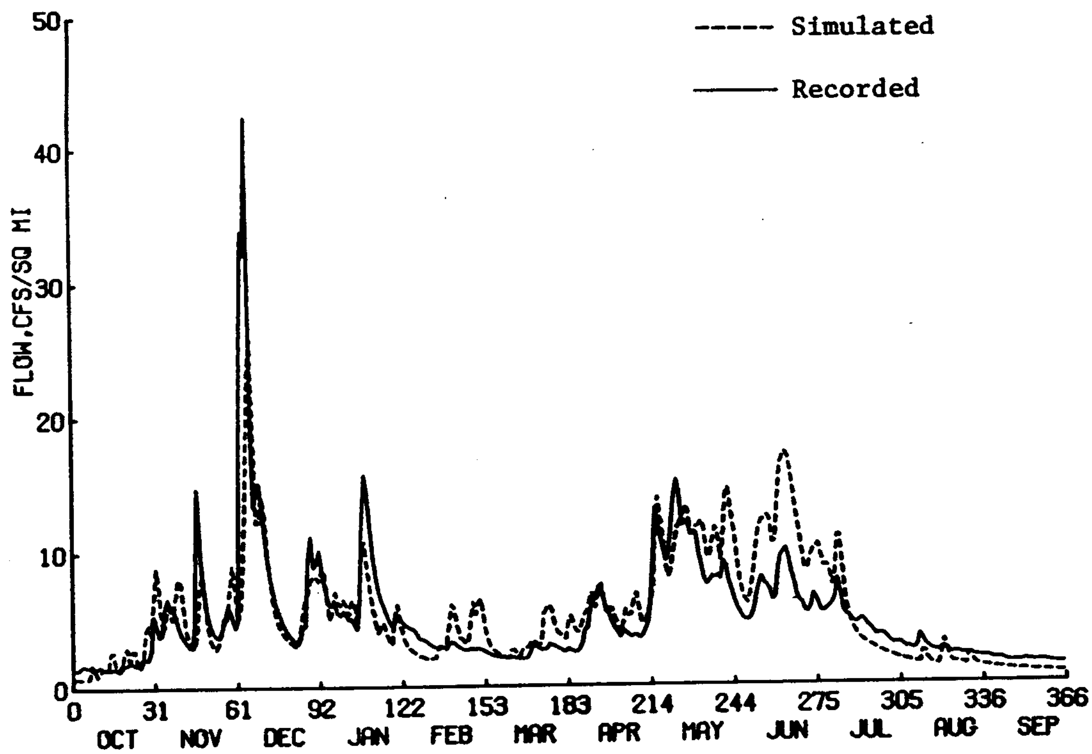

Figure 8(d). Simulated and observed runoff at U.S.G.S. station 14-2325 (Cispus River near Randle), water year 1976.

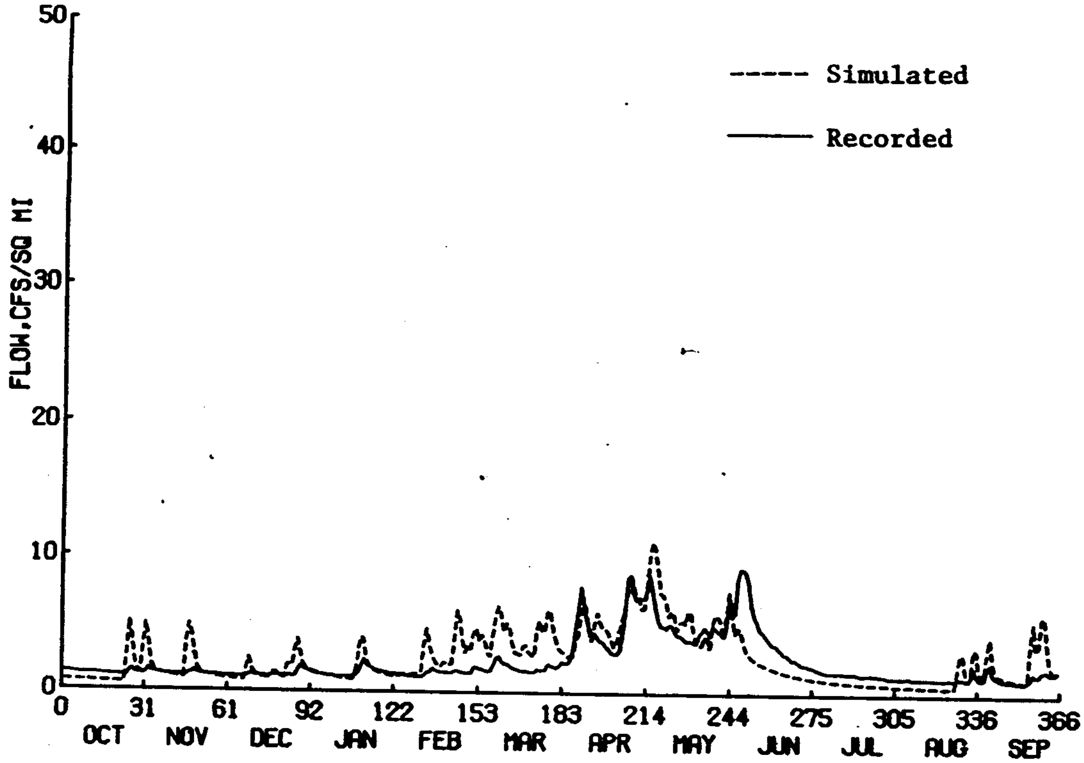

Figure 8(e). Simulated and observed runoff at U.S.G.S. station 14-2325 (Cispus River near Randle), water year 1977.

Results

Forecast results for the period 1950-78 were obtained for two forecast seasons, March 1 - July 31, and April 1 - July 31. Forecast period precipitation was chosen to represent an average scenario only. This choice was made in the interest of reducing computational expense, and because the results for the Cedar River showed that the high and low scenarios often did not bracket the runoff which actually occured. A better approach to estimation of confidence bounds for forecasts appears to be a statistical analysis of past forecasts, or perhaps an extension of the method proposed by Young, et al. (1980). Another change from the Cedar River analysis was that the forecast period precipitation scenario was taken as a composite of monthly sequences from those years of the historic record having closest to the long term average precipitation for the given month. This avoids the problem of choosing between years which have similar forecast season total precipitation, but vastly different timing.

As a result of the bias in the verification period noted in the previous section, (forecast season runoff biased upward), corrections for the forecasts were sought. Two adjustments were considered; an additive and a multiplicative corrector. The additive corrector may be expressed as

$$\hat{R}' = \hat{R} + \gamma_a$$

and the multiplicative corrector as

$$\hat{R}'' = \gamma_m \hat{R}$$

The parameters γ_a and γ_m must, of course, be estimated. Although it is tempting to estimate the parameters via regression from the entire 29 year test period, such an approach is not defensible on statistical grounds. The preferred approach is the split sample method, as used in estimation of HM model forecast accuracy. This method, which insures that only observations prior to the year analyzed are used in estimation of the correction parameters was applied for independent estimation of the two parameters. Although a simple linear regression of forecasted against actual runoff might be expected to improve the accuracy beyond that obtained using the additive and multiplicative corrections alone, the sample size was not considered large enough to allow estimation of two parameters.

Tables 12(a) and 12(b) give observed forecast period runoff and forecasted runoff for both the uncorrected NWS model results and the two corrected estimates for the period 1958-78. The period 1950-57 was used for initial estimation of the corrections applied to early years in the record, and so was not included in the analysis. Coefficients of prediction for the three forecast sets, along with results obtained from the HM model are presented

Table 12(a). Observed and Forecasted Runoff, Cispus River, March 1 - July 31 (in inches).

Year	Observed	Raw Forecast	Additive Correction	Multiplicative Correction
1958	23.93	30.11	24.69	25.97
1959	25.67	33.60	28.18	28.98
1960	28.97	25.40	19.98	21.90
1961	32.32	36.34	31.44	31.42
1962	26.11	27.96	23.06	24.18
1963	21.86	22.23	17.33	19.22
1964	32.32	37.09	32.79	32.59
1965	28.50	45.77	41.47	40.22
1966	32.20	31.99	27.69	28.11
1967	29.76	42.02	37.20	36.30
1968	23.94	28.89	24.07	24.96
1969	33.16	39.29	34.47	33.94
1970	25.44	32.47	27.20	27.65
1971	42.05	51.04	45.77	43.47
1972	55.00	64.51	59.24	54.94
1973	17.74	24.20	18.51	20.50
1974	49.76	47.55	41.86	40.29
1975	33.71	45.11	39.42	38.22
1976	32.01	46.73	41.10	39.44
1977	20.28	18.27	12.64	15.42
1978	24.23	33.25	27.62	28.06

Table 12(b). Observed and Forecasted Runoff, Cispus River, April 1 - July 31 (in inches).

Year	Observed	Raw Forecast	Additive Correction	Multiplicative Correction
1958	23.35	23.16	16.09	19.12
1959	22.44	29.59	22.52	24.42
1960	24.63	22.44	15.37	18.52
1961	26.05	28.56	22.98	24.33
1962	23.50	23.90	18.32	20.36
1963	18.43	17.28	11.70	14.72
1964	29.64	35.25	30.74	30.91
1965	24.24	34.53	30.02	30.28
1966	28.18	28.57	24.06	25.05
1967	25.98	35.96	31.29	31.20
1968	18.41	20.69	16.02	17.95
1969	30.00	32.59	27.92	28.28
1970	20.83	25.09	20.38	21.64
1971	38.29	49.22	44.51	42.46
1972	40.21	61.91	57.20	53.40
1973	14.80	17.24	11.54	14.57
1974	44.59	45.58	39.88	38.52
1975	29.11	39.39	33.69	33.29
1976	29.20	42.62	37.05	36.03
1977	18.18	17.13	11.56	14.48
1978	20.20	25.62	20.05	21.66

in Figure 15. The low C_p's for the unadjusted forecasts are largely a result of simulation bias in the forecast period. The multiplicative correction yields better results for both forecast periods. The drop in forecast accuracy from March 1 to April 1 is unusual, and does not follow the pattern of HM model results for either the Cispus basin or for a number of other Northwest rivers which have been analyzed. However, HM model accuracy for this basin is less than that obtained for many other rivers in the region, probably resulting from the absence of good low elevation precipitation stations, and perhaps as a result of heterogeneity of storm patterns in the basin. The influence of Mt. St. Helens and Mt. Adams on precipitation patterns in the basin may be an important factor as well. In any event, it appears that the accuracy of forecasts obtained using the NWS models for this basin is, at best, comparable to that obtained using the much simpler HM model, and there is certainly no evidence that the NWS model forecasts are superior.

In Chapter 4, some additional analysis of forecast results is performed to address the question of possible differences in forecast accuracy between models in drought years. Also considered is the issue of calibration error for conceptual models, and its impact on potential improvements in forecast accuracy.

Chapter 4

FORECAST MODEL COMPARISON

The forecast results for the Cedar and Cispus Rivers discussed in Chapters 2 and 3 indicate no clear differences in forecast accuracy for either model. These comparisons, however, make no attempt to distinguish forecast errors by the characteristics of the individual years, such as the level of actual runoff. In this chapter, consideration is given to the possibility of differences in error magnitude and/or sign for extreme low runoff years, when forecast accuracy tends to be most critical in the Northwest. Another question, which was addressed subjectively in Chapter 1, is the extent of potential accuracy improvements. For conceptual deterministic models, such as the NWS models, it is possible to address the inverse of this question, i.e., to estimate the maximum possible forecast accuracy given various levels of simulation error. Insofar as simulation error is related to the data base supporting the model, the potential for forecast accuracy improvements, which might be related to improvements in data acquisition, can subsequently be inferred.

Forecast Comparison for Extreme Years

Although the period for which forecasts were compared (1958-78) is short, it does include several years of extreme low flow. Water year 1977, in particular, was the lowest runoff year of record for many Northwest streams; for instance runoff of the Columbia River at the Dalles was the lowest in a record dating from 1978. Ohter extremes in the period of analysis include 1973, 1968, and 1963. Although one might also wish to consider forecast error for years of extreme high flow, this is not as important for most Northwestern U.S. streams, with several notable exceptions such as the Okanagon River, flood damage usually is not associated with spring snowmelt.

It is not possible to conduct a rigorous statistical analysis on the basis of the small number of extremes which are available for analysis; however some general indications of model performance can be obtained. This is best done graphically by plotting forecast versus recorded runoff for the two models. Figures 9 and 10(a) and (b) show such results for the Cedar River (April 1 - July 31 forecast season) and the Cispus River (March 1 - July 31 and April 1 - July 31) plotted in this manner. Also plotted are envelopes of 10% forecast error; this is the one standard deviation envelope for forecast accuracy $C_p = 0.75$ when the seasonal runoff coefficient of variation is 0.2, which is approximately the April - July seasonal value for both streams.

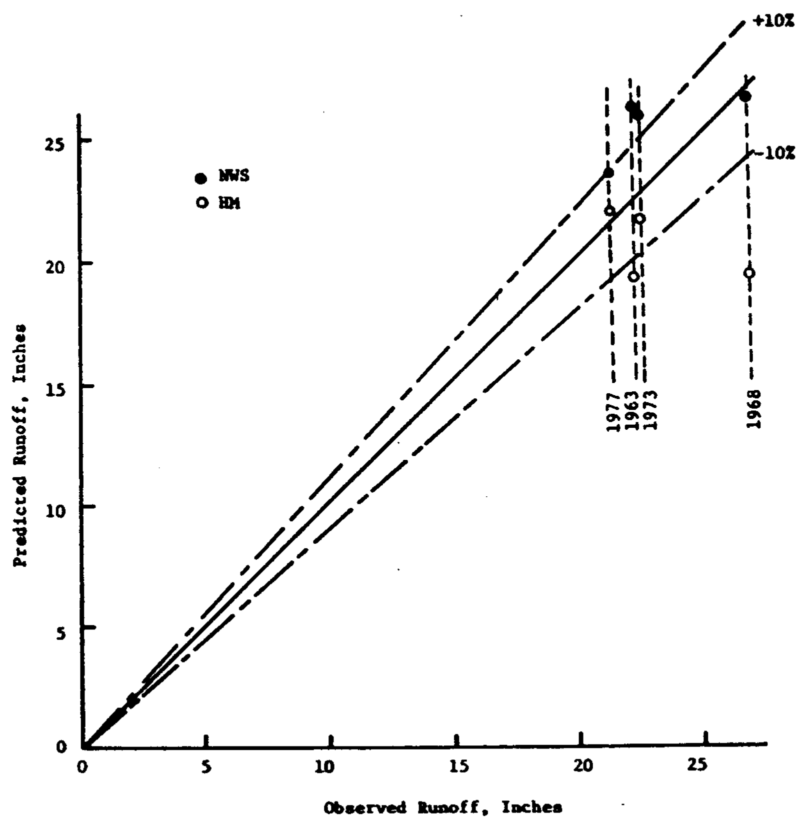

Figure 9. April 1 - July 31 Forecast accuracy comparison, Cedar River, for extreme low runoff years 1963, 1968, 1973, 1977.

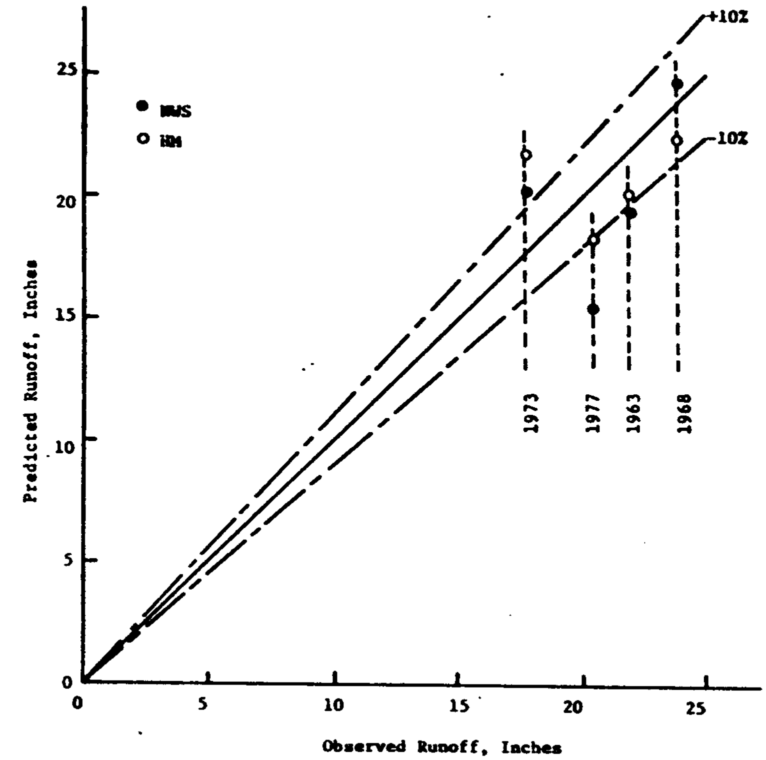

Figure 10(a). March 1 - July 31 Forecast accuracy comparison, Cispus River, for extreme low runoff years 1963, 1968, 1973, 1977.

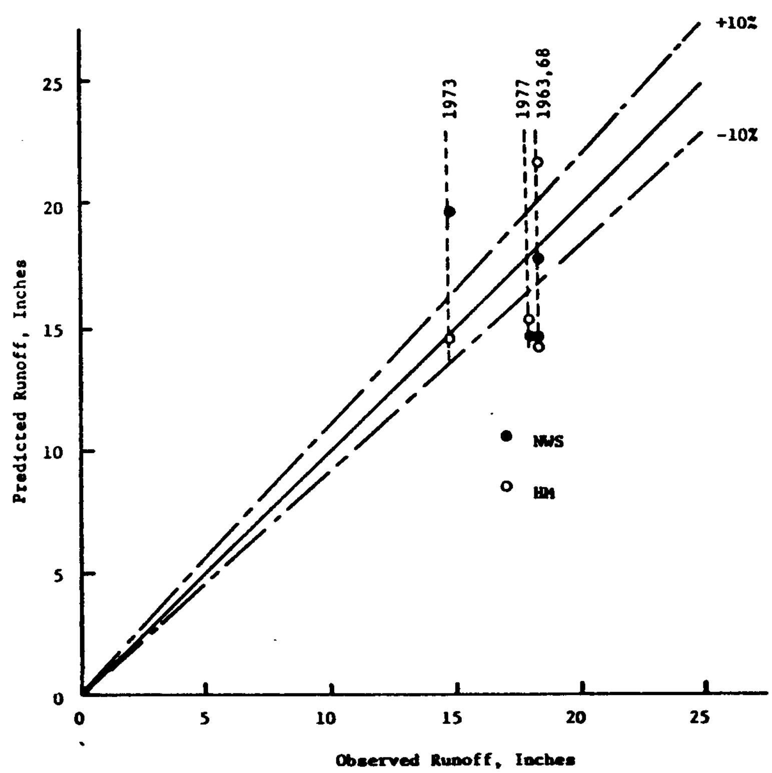

Figure 10(b). April 1 - July 31 Forecast accuracy comparison, Cispus River, for extreme low runoff years 1963, 1968, 1973, 1977.

The Cedar River results indicate an apparent tendency for underestimation by the HM model, although this resulted in an abnormally large error only in 1968. The NWS model tended to forecast higher than the HM model runoff, and overforecasting in two years suggests the possibility for improvement in accuracy by use of an average of the two methods. For earlier forecasts the errors will normally have the same sign, since they are more heavily influenced by differences between 'average' forecast period precipitation, assumed by both models, and the rainfall actually occuring. However, by April 1, most precipitation leading to runoff has already occured, and the dominant error source is in estimation of storage.

The Cispus River results show no apparent bias for the NWS forecasts and a tendency for the errors for both models to have the same sign, especially for the March 1 forecast. There is some tendency for underforecasting by the HM model, although this is not as apparent as for the Cedar River forecasts. There is no evidence for either stream of differences in error magnitude; the tendency for underforecasting by the HM model is the only obvious difference in model performance for the four years considered.

Forecast Accuracy Limitation

The work presented in this report gives an indication of the forecast accuracy practically obtainable through use of conceptual deterministic models. One question which inevitably confronts the user of such models is the extent to which simulation error, i.e., the difference between simulated and recorded runoff (when precipitation and temperature are known) contributes to forecast error. In Chapters 2 and 3, for instance, we have included results showing that monthly simulation error, expressed as mean absolute error, is in the vicinity of 15% averaged over the year for the Cedar River, and somewhat higher for the Cispus. Assuming that the model user has adequately calibrated the model, simulation error is largely dependent on data availability. Johansen (1971) has shown, for instance, that simulation error decreases rapidly with addition of precipitation stations for up to about 3 gages in a basin, and less rapidly as larger numbers of stations are used. Similar results were obtained by Wilson, et al. (1979).

One can consider the two basins tested here as typical of many in the mountainous regions of the Pacific Northwest, with no gages within the basin. For this reason, the simulation errors achieved may have broader implications for use of conceptual deterministic models for extended streamflow prediction elsewhere. Interest will be focused on those cases where simulation error limits forecast accuracy, implying the need for additional data collection to make use of conceptual deterministic models practical. In the remainder of this section the relationship between simulation error and maximum forecast accuracy is developed, and discussed in light of the results from Chapters 2 and 3.

As an upper limit on forecast accuracy, one can consider the case where the forecast period precipitation and temperature are known (perfect meteorological forecast) so that the forecast error is comprised of simulation error only. In this analysis, the coefficient of prediction is used as the measure of forecast accuracy,

$$C_p = 1 - \frac{E(R_f - \hat{R}_f)^2}{\sigma_s^2}$$

where E is the statistical expectation, R_f and $\hat{R}_f$ are forecasted and observed runoff, respectively, and σ_s^2 is the variance of the forecast period runoff. It is useful to consider the term $CV_s^2 = \frac{E(R_f - \hat{R}_f)^2}{R_s^2}$, or the squared coefficient of variation of the forecasted (simulated) runoff, where R_s is mean forecast period runoff. The numerator may be expressed as the sum of the daily run-off volumes in the forecast period if the notation $R_f = \sum_{i=1}^{n} x_i$, $\hat{R}_f = \sum_{i=1}^{n} \hat{x}_i$ is used. Expanding the seasonal error variance, $E(R_f - \hat{R}_f)^2 =$

$$E[\sum_{i=1}^{n}(x_i - \hat{x}_i)^2] = E\{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2 + 2\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}(x_i - \hat{x}_i)(x_j - \hat{x}_j)\}$$

The first factor is the summed variance of the monthly forecast errors, which can be expressed as the squared coefficient of variation of the monthly simulation error multiplied by the mean monthly runoff $(\overline{x}_i)$ squared. The second term is the covariance of the monthly forecast error, which can also be expressed in terms of the coefficient of variation. Making the assumption that the coefficients of variation of the monthly errors are identical, and denoting the coefficient of variation as CV_m, the forecast error variance becomes

$$E(R_f - \hat{R}_f)^2 = CV_m[\Sigma \overline{x}_i^2 + \sum_{i=1}\sum_{j=i+1}\rho_{ij}\overline{x}_i\overline{x}_j]$$

where ρ_{ij} is the correlation of the simulation error in month i with that of month j. A convenient form of the monthly simulation error covariance is $\rho_{ij} = \rho^{|i-j|}$, or lag one Markov. If the divisor in the original relationship for CV_s^2 is now reintroduced, and the assumptions suggested above included, the result is

$$CV_s^2 = CV_m^2\{\frac{\Sigma\overline{x}_i^2}{R_s^2} + 2\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\rho^{|i-j|}\frac{\overline{x}_i\overline{x}_j}{R_s^2}\}$$

Now define the fractions $f_i = \frac{\overline{x}_i}{R_s}$ or the average fraction of forecast period runoff occuring in month i. This results in

$$CV_s^2 = CV_m^2 \{ \Sigma f_i^2 + 2 \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \rho^{|i-j|} f_i f_j \}$$

Considering again the coefficient of prediction, the result is

$$C_p = 1 - \frac{E(R_f - \hat{R}_f)^2}{\sigma_s^2} = 1 - \frac{CV_s^2 R_s^2}{CV_s^{*2} R_s^2} = 1 - \frac{CV_s^2}{CV_s^{*2}}$$

where CV_s^* is the coefficient of variation of forecast period natural runoff, and CV_s is the coefficient of variation of forecast period error.

This relationship indicates that the contribution of simulation error to forecast accuracy is dependent on (a) the coefficient of variation of monthly simulation errors, (b) the correlation between monthly simulation errors, and (c) the fractional distribution of forecast period runoff. This relationship is plotted in Figures 11(a)-(e) as a function of forecast date,

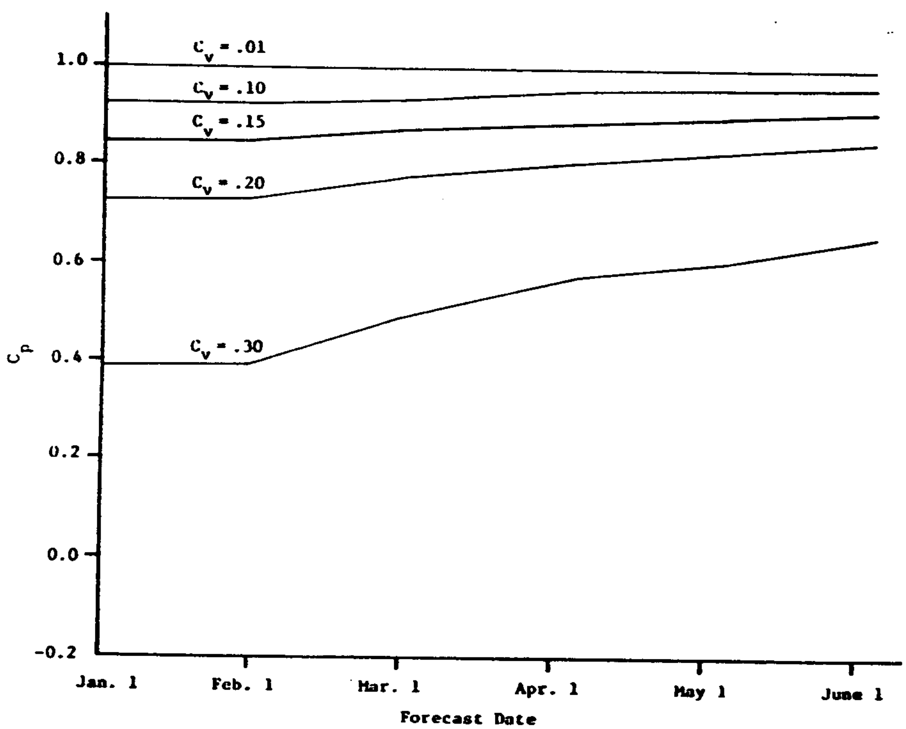

Figure 11(a). Limiting coefficient of prediction for seasonal forecasts from date indicated through July 31 assuming perfect precipitation forecast, as function of monthly error coefficient of variation and lag one correlation coefficient ρ = 0.0.

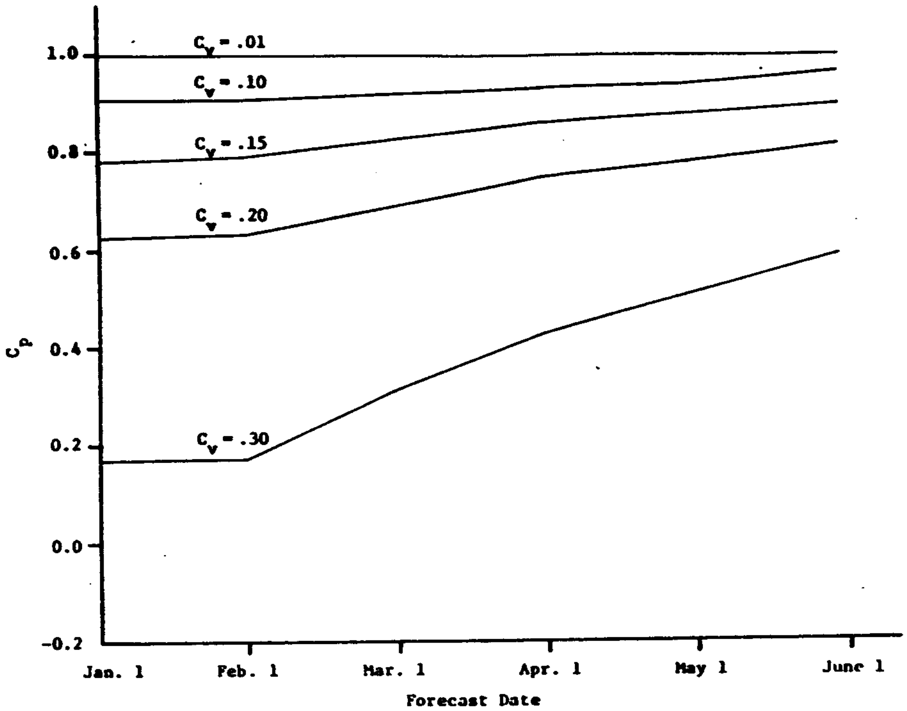

Figure 11(b). Limiting coefficient of prediction for seasonal forecasts from date indicated through July 31 assuming perfect precipitation forecast, as function of monthly error coefficient of variation and lag one correlation coefficient $\rho = 0.4$.

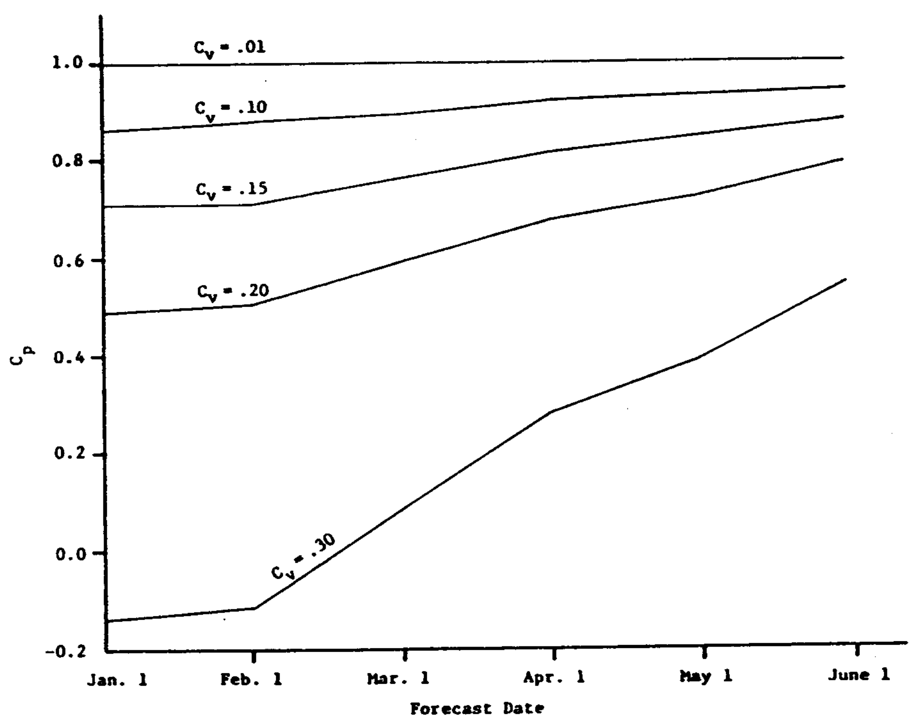

Figure 11(c). Limiting coefficient of prediction for seasonal forecasts from date indicated through July 31 assuming perfect precipitation forecast, as function of monthly error coefficient of variation and lag one correlation coefficient $\rho = 0.6$.

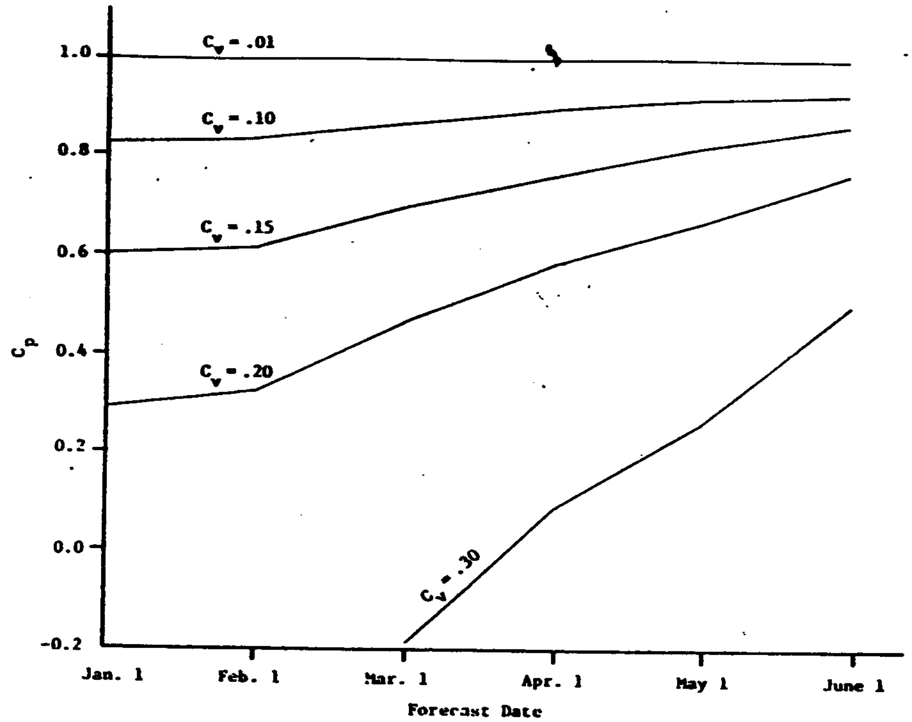

Figure 11(d). Limiting Coefficient of prediction for seasonal forecasts from date indicated through July 31 assuming perfect precipitation forecast, as function of monthly error coefficient of variation and lag one correlation coefficient $\rho = 0.8$.

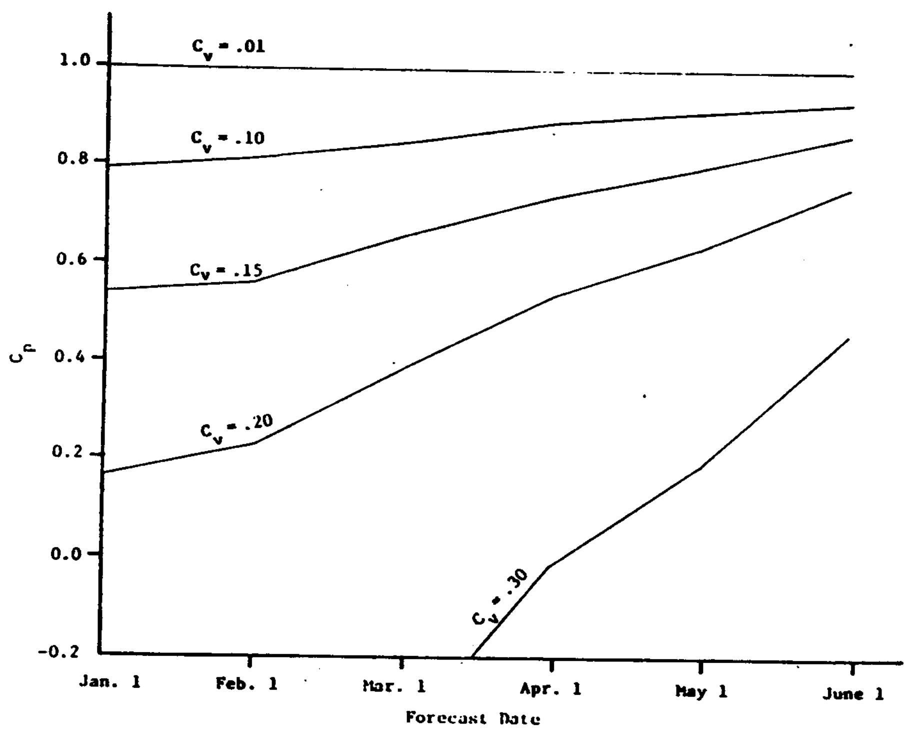

Figure 11(e). Limiting coefficient of prediction for seasonal forecasts from date indicated through July 31 assuming perfect precipitation forecast, as function of monthly error coefficient of variation and lag one correlation coefficient $\rho = 0.9$.

where the subscript has been dropped from CV_m, the monthly simulation error coefficient of variation. The relative runoff fractions, f_i, were taken from the historic record of the Columbia River at the Dalles and are typical of many Northwest streams. Although a large range of coefficients of variation and correlation coefficients are included, results from Chapters 2 and 3 suggest that attention should be focused on the range $.10 \leq CV_m \leq .15$ as a potentially attainable error level (as a rough index, it should be noted that, for the normal probability distribution, the mean absolute error, used as an estimator in Chapters 2 and 3, is about 80% of a standard deviation). Similarly, the higher values of the lag one correlation coefficient, ρ, are probably most realistic. High correlations are indicated by the persistence in simulated runoff structure; simulation errors in the spring runoff period tend to be related to errors in estimation of basin storage, and so persist throughout the period.

Focusing attention on the suggested parameter ranges, it is apparent that simulation error becomes the dominant contribution to forecast error as the forecast date moves from winter to spring. For an April 1 forecast, with monthly simulation error CV = .15 and ρ = .4 (the latter a conservative value) the maximum possible C_p is about 0.85. This is only slightly larger than the value obtained by the HM model for real forecasts, which, of course, include all sources of error. Earlier in the year, simulation error is not as important, and maximum C_p values are much higher than those which can actually be achieved. This reflects the importance of ignorance of future precipitation, and the improvement in runoff forecasts which might be attainable through improved meteorological forecasting.

Although some refinements might be made in the analysis (for instance, a detailed analysis of simulation error persistence structure) the analysis does indicate the importance of simulation accuracy to forecast accuracy when conceptual deterministic models are used for extended prediction. As a general indication of the accuracy levels which might be achieved, a monthly simulation error coefficient of variation of 0.15 for a poorly gaged mountain watershed is respectable, and a coefficient of variation of 0.10 is about the best which is likely to be achieved with existing precipitation networks, this suggests that the issue which must be addressed in selection of a forecasting model is the level of complexity which can be supported by the data base.

CHAPTER 5

CONCLUSIONS

The forecast accuracy comparisons reported here are the first known to the authors which attempt to estimate the statistical properties of seasonal forecast errors for conceptual simulation models used in extended streamflow prediction mode. The results fail to indicate a clear preference for the conceptual models tested (NWS) when compared to a simpler storage accounting index model (HM), for which error statistics have been estimated previously at a number of sites. In this light, it is useful to review the logistical requirements for the two models, and the type of information provided.

Implementation of either model requires an initial data gathering and editing stage. For the present purposes, the existence of a single stream gage at the forecast point is assumed, as was the case for both sites considered. Streamflow data are normally available from the US Geological survey in card image format on magnetic tape, and often require minimal screening if the gage record is unfragmented. Both the NWS and HM models have been altered to allow direct input of the data in the USGS format, so no reformating is necessary.

At the data gathering stage, precipitation/temperature as well as snow course records must be identified. These data, which are available from the National Environmental Data Service on magnetic tape, are not in a readily usable format, and must be transcribed to a format similar to the streamflow data. Usually, a prelimary screening procedure, using as the principle criterion completeness of records, will identify precipitation and temperature stations. These remaining records must be edited to estimate missing data. This is a time consuming process, which we have found is not well suited to automation because of the variety of patterns which missing data sequences can form. We have found the most effective method for estimating missing data is to interactively search the files for missing data codes, then to estimate missing data using adjacent observations for short periods of missing record, and nearby stations for longer missing periods. This procedure is required only for precipitation if the HM model is used (although Tangborn (1978) describes an adaptation of the model which uses temperature data, this version is more suitable for short term forecasting). Following data editing, a screening procedure, described in Chapter 3, is used for the HM model, and forecasts can be made directly.

Use of the NWS model requires six hour precipitation and temperature data as model input. Where only daily precipitation and temperature maxima and minima are available, which is the case for many climatalogical stations, the disaggregation procedure described in Chapter 3 must be used. Subsequently, division of the basin into elevation zones must be performed, which requires estimation of a hypsometric curve. Additional manpower is required to estimate temperature and precititation for each six hour period for each zone. For a basin where four elevation zones are used, this results in 32 input files, in addition to the runoff file, as opposed to only two for the HM model.

Model calibration of the NWS model is a two stage procedure, where initially the input precipitation and temperature are used to drive the snowmelt model. In the form used here, snowmelt model output (rain plus melt) is aggregated to a daily time increment, compatible with the runoff model. The rain plus melt records are then routed through the runoff model, simulated runoff checked against recorded, and parameters modified accordingly. This procedure is fairly time consuming and expensive. It should be noted that the National Weather Service's on-line simulation package links the snowmelt and soil moisture accounting models so that calibration can be streamlined somewhat.

Total computer cost of the analysis conducted here for the NWS model was about $500 for each of the three runs (Cedar River and two forecast periods for the Cispus) on the University of Washington CDC Cyber 750. Using the HM model, equivalent results can be obtained for about $2. Operational forecasts using the NWS model are less costly, since fewer years of record need be run; once the model has been calibrated and verified, forecast cost, including file updating, is in the vicinity of $20, whereas the cost of HM operational forecasts is almost negligible (under $1). For comparison purposes, it should be noted that the figures used are based on academic computing rates, which are considerably cheaper than the commercial equivalent.

Perhaps more important than the direct computing cost, from a comparative standpoint, is the time required for file manipulation, and the opportunities for mistakes. All of the files used for both NWS and HM models must be updated as forecasts are made throughout the snowmelt season. Because of the number of files involved for the NWS model, an automated system for performing the updating is advisable; this requires the development of additional software. For the HM model, where only two files are involved, manual updating is feasible.

Given the lack of evidence of forecast accuracy improvement using the conceptual models, and the great difference in logistical requirements, an obvious question is whether and under what circumstances conceptual models should be used for extended streamflow prediction. One consideration may be the difference in the type of information provided by the two forecasting methods. The HM model provides a forecast of cumulative runoff volume, and estimated basin water storage at the time of the forecast. The NWS model provides a time history of soil moisture in several zones in addition to runoff. The model also provides an estimate of the short term (daily) runoff response of the basin conditioned on forecast period meteorological conditions. This information may prove useful to the forecaster in "adjusting" forecasted runoff to reflect the behavior of the basin under past similar conditions, and in evaluating the impact of alternate hydrometeorological scenarios.

As noted in Chapter 4, simulation error, which is reflected in errors in estimation of the contents of the storage zones, is usually the most important source of forecast error. This suggests that one possibility for improving conceptual model-based forecast is to update the storage estimates based on pre-forecast runoff data. Kitanidis and Bras (1980 a,b,c) have developed such an approach, which makes use of state estimation techniques to perform the updating. In the work reported, short term forecast accuracy improvements (e.g. flood forecasts) were achieved through use of updating applied to a simplified version of the NWS soil moisture accounting model. A useful extension of this work may be to incorporate such a scheme in a seasonal forecasting framework.

One other situation in which use of conceptual models may be waranted is forecasting seasonal runoff for basins with short record lengths. The HM model uses least squares methods for parameter estimation, hence one component of forecast error is parameter estimation error, which decreases as the inverse of the square root of the record length. For sufficiently long records, parameter estimation error becomes less significant than model error (i.e. the effect of the simplifying assumptions incorporated in the model structure) and uncertainly in forecast period precipitation. However, for record lengths less than about 20 years, parameter estimation error becomes important. Parameter estimation for conceptual deterministic models, on the other hand, is not improved much when the record length is increased beyond about five years, especially if the period of record includes a range of high and low years. Normally a verification period is required in addition to the calibration period, however, a typical eight-year period of record might be divided into four years for calibration and four for verification, which is much less than would be considered a minimum for least squares parameter estimation.

The short record length situation may prove to be the most beneficial use for conceptual models in seasonal snowmelt forecasting; where longer periods of record exist it is likely that the use of such models cannot be justified. This is especially true in view of the greatly increased logistical requirements and lack of evidence for forecast accuracy improvements.

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