INFLUENCE OF ELEVATION ON REGIONAL EVAPOTRANSPIRATION
USING MULTIVARIATE GEOSTATISTICS FOR VARIOUS
CLIMATIC REGIMES IN OREGON

by

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ABSTRACT

This article investigated the application of multivariate geostatistics for analysis of regional evapotranspiration. The focus of the described research was analysis and modeling of the spatial correlation between evapotranspiration and elevation above sea level. The main goal was to investigate whether the use of cokriging could improve the accuracy of evapotranspiration estimates over a regular grid by including elevation in the estimation procedure.

A total of 11 study cases for each of four different climatic regions (Willamette Valley, North Central, South Central and East) within the state of Oregon were analyzed. Long-term monthly (February to November) averages of daily reference evapotranspiration (ET_r) and values of annual ET_r were available at 199 locations within the regions. Values of elevation were available at the 199 locations and at 8570 additional locations on a grid of approximately 5 km per side.

Experimental direct- and cross-semivariograms were computed to describe the spatial variability of ET_r and elevation and their correlation. Experimental direct-semivariograms for ET_r were fit with isotropic spherical models with small nugget effects. Experimental direct-semivariograms for elevation were fit with isotropic models with nugget effects and two nested structures (spherical and gaussian) for the Willamette Valley region, one structure (spherical) for the North Central region, and two nested structures (spherical and linear) for the South Central and East regions. The experimental cross-semivariograms were fit with isotropic spherical models.

Monthly and annual ET_r values were estimated at 8570 locations on a 5 km grid by using kriging and cokriging in conjunction with the previously fit direct- and cross-semivariograms. Kriging and cokriging estimation error standard deviations were computed for each study case at those 8570 locations. ET_r estimates and estimation error standard deviations were plotted as contour maps. Maximum, minimum and

average kriging and cokriging estimates of ET_r were in general agreement, although minimum and average values tended to be lower for cokriging. However, contour lines of cokriged ET_r reflected more closely the elevation features of the climatic regions. Maximum and average estimation error standard deviations were lower for cokriging, although minimum values were very similar for both kriging and cokriging. Average cokriging standard deviations decreased by about 20 to 30 % in the Willamette Valley and North Central regions and by 5 to 13 % in the South Central and East regions. These differences between regions were due to the lower correlation coefficients between ET_r and elevation observed in the latter two regions. Contour maps of standard deviations showed cokriging had a more uniform distribution of estimation errors than kriging, for which errors tended to decrease in the vicinity of the sample ET_r points at the weather stations. Errors increased along regional borders for both kriging and cokriging, although maximum estimation error values were lower for cokriging.

INTRODUCTION

A quantitative evaluation of evapotranspiration is required to solve various natural resource problems, including hydrologic balance studies, management of water resources, and environmental assessments. More accurate estimates of crop water use are critical for improving the efficiency of irrigation systems and irrigation scheduling. For irrigation, evapotranspiration is generally estimated on the basis of meteorological parameters recorded at a weather station located at a site considered representative of the project area. The fields to be irrigated are generally orders of magnitude larger than the supposedly representative weather station site. The local evapotranspiration estimates must therefore be extrapolated to areas located at substantial distances from the weather station site. Other relatively recent developments have also resulted in an increased interest in regional scale evapotranspiration. One is the

availability of remotely sensed data of surface conditions which can be coupled with regional evapotranspiration estimates in hydrologic balance studies. Second is the increasing worldwide concern in the prediction of both short- and long-term climatic changes at the global scale.

Efforts to improve the accuracy of regional evapotranspiration estimates and to quantify the error associated with the application of a local estimate to a region a certain distance away must rely on a model of the spatial variability of evapotranspiration (Cuenca and Amegge, 1987), i.e. the change in evapotranspiration with respect to the distance between weather stations at which meteorological data are collected. Such a model should consider the topographic characteristics of the region as changes in elevation above sea level within a region may significantly affect the structure of the spatial variability of evapotranspiration (Nuss, 1989).

Most of the extrapolation techniques commonly used give arbitrary weights to the data, regardless of the physical aspects of the problem, and cannot provide any indication as to the precision of the results (Delhomme, 1978). The theory of regionalized variables, or geostatistics, uses the correlation between neighboring measurements to construct a model which characterizes the structure of the spatial variability of the parameter under study, such as evapotranspiration (Journel and Huijbregts, 1978). The modeled spatial variability can be applied to estimate the required parameter by spatial extrapolation at locations where no measurements are available. The method also provides a tool to quantify the error of the estimation (Delhomme, 1978).

The feasibility of applying geostatistics to evapotranspiration studies has been previously analyzed for the state of Oregon (Cuenca and Amegge, 1987). This research indicated the presence of a bias in the estimates derived from the application of geostatistics due to the fact that the topographic characteristics of Oregon were not included in the modeled spatial variability. Cuenca and Amegge (1987)

suggested dividing the state into uniform climatic regions and applying geostatistics within each region. This task was performed by Nuss (1989) with an improvement over the original work, but topographic characteristics were again excluded.

The scope of the work described in this article was limited to the state of Oregon. The general objective was to analyze and model the spatial correlation between local estimates of evapotranspiration and values of elevation above sea level. The main goal was to investigate the improvement in accuracy in the estimates of evapotranspiration over a regular grid by including the effects of elevation using a multivariate geostatistical approach. The final product was the contour map of these estimates of evapotranspiration for those climatic regimes in Oregon in which the analysis technique was feasible. This work focused on the spatial variability of reference evapotranspiration (ET_r), defined as "the rate of evapotranspiration from an extensive surface of 8 to 15 cm, green grass cover of uniform height, actively growing, completely shading the ground, and not short of water" (Doorenbos and Pruitt, 1977).

MATERIAL AND METHODS

Description of the ET_r and elevation data bases

Six climatic regions were identified in Oregon based on general climatic characteristics (Redmond, 1985). The present study was limited to four of those regions and the other two regions were excluded due to the small number of stations and the lack of significant correlation between ET_r and elevation (Martínez-Cob, 1990). The four regions studied (Figure 1) were: A) Willamette Valley; B) North Central; C) South Central; and D) East.

Long-term monthly averages of daily mean air temperature were recorded at 57, 41, 52 and 49 primary data weather stations, respectively, for regions A to D. Long-term monthly averages of daily minimum air relative humidity, daily ratio of actual to maximum possible sunshine hours, and daily

daytime wind speed at 2 m height were available at 16, 21 and 27 secondary data weather stations, respectively, within the four regions, and extrapolated to the 199 primary data weather stations (Martínez-Cob, 1990). This extrapolation was performed using an inverse squared distance technique (Isaaks and Srivastava, 1989) because the small number of secondary data weather stations did not allow for enough data pairs to model a semivariogram with confidence. These meteorological data bases were used to compute local values of long-term monthly averages of daily ET_r (mm d^{-1}) and long-term values of annual ET_r (mm) for each primary data weather station, with the FAO-USDA Blaney-Criddle method (Doorenbos and Pruitt, 1977; Allen and Pruitt, 1986; Cuenca, 1989). The months of January and December were excluded from further analysis because values of ET_r were zero at most of the primary data weather stations (Martínez-Cob, 1990).

Elevation values were available at the sites at which the primary data weather stations were located (Redmond, 1985). Additional elevation values were available on a grid of approximately 5 km per side at 1360, 1504, 3181 and 2525 points, respectively, for regions A to D (Figure 1), selected from the digital elevation model produced by the U.S. Defense Mapping Agency.

Geostatistical analyses

In this work, there were a total of 44 study cases as ten sets of monthly ET_r values (February to November) and one set of annual ET_r values were analyzed within each of the four regions studied. For each of the study cases, the geostatistical analysis involved several steps (Journel and Huijbregts, 1978): 1) semivariogram modeling and validation; 2) kriging and cokriging; and 3) mapping of ET_r and errors.

Semivariogram modeling and validation

Semivariograms are the geostatistical tools which describe the spatial variability of the variables of interest and their spatial correlation. For each of the 44 study cases, it was required to model a direct-semivariogram for ET_r and a

cross-semivariogram. For the 11 cases studied within a single region, the same direct-semivariogram for elevation was modeled.

The first step to model semivariograms was the computation of experimental direct- and cross-semivariograms (David, 1977; Journel and Huijbregts, 1978). In all cases, isotropy was assumed and isotropic experimental semivariograms were computed even though anisotropy was evident for elevation (Martínez-Cob, 1990). The relatively small sample size for ET_r within each region precluded the computation of anisotropic experimental direct-semivariograms for ET_r and cross-semivariograms unless very wide angle and distance classes were used, resulting in a loss of directional resolution. Likewise, the convenience of a simplified semivariogram model and model consistency between the two regionalized variables under study (Hevesi et al., 1991) indicated that computation of isotropic experimental semivariograms was more appropriate in this study.

The theoretical models fit to the experimental semivariogram values must be conditionally positive-definite functions (Journel and Huijbregts, 1978; Armstrong and Jabin, 1981). In the case of direct-semivariograms, it suffices to adhere to those models for which the conditionally positive-definite condition has been shown (Armstrong and Jabin, 1981). In the case of cross-semivariograms, positive-definite curves (PDC) provide an invaluable graphical test of the conditionally positive-definite condition (Hevesi et al., 1991).

Model parameters (nugget effect, sill and range) were estimated visually. The cross-validation procedure was performed to check the validity of the model. The estimated parameters of the model were then modified in a "trial-and-error" procedure until adequate cross-validation statistics were obtained. To cross-validate a semivariogram model, a sample was deleted from the data set of one variable, and kriging or cokriging were used to estimate the value of that variable at the location of the deleted sample. This

estimation was done using the remaining samples and the selected semivariogram model and parameters. Differences between estimated and experimental values were summarized using the cross-validation statistics (Cooper and Istok, 1988): average kriging (or cokriging) error (AKE), mean squared error (MSE), and standardized error variance (SMSE). A model was considered to ensure unbiased estimates if the AKE was close to zero and was considered accurate if the MSE was, as a practical rule, less than the variance of the sample values (Cooper and Istok, 1988). The SMSE indicated the consistency of the calculated estimation error variances with the observed MSE. Model validity was satisfied if the SMSE was within the interval $1 \pm 2\sqrt{2/n}$ (Delhomme, 1978) where n was the sample size. Table 1 lists the cross-validation criteria for the different semivariogram ET_r models to be accepted as adequate.

Kriging and Cokriging

The different cross-validated semivariogram models were used to estimate values of ET_r by applying ordinary point kriging and cokriging techniques, which provide the best linear estimator of a particular variable of interest at a point where it is unknown (Journel and Huijbregts, 1978). At a regional level, it would have been reasonable to use block kriging and cokriging to estimate the mean value of the variable of interest over a block, an area smaller than the whole region or domain from which data have been collected. Block kriging and cokriging are generally preferred over point kriging and cokriging for regional analysis but they are more computationally intensive (Isaaks and Srivastava, 1989). Limitations caused by the practicality of efficiently carrying out computations for the 8570 data points precluded the use of geostatistics interpolation techniques other than point kriging and cokriging.

In kriging, the unknown value of ET_r , $z_1^*(x_0)$ at a point x_0 was estimated by a linear combination of n_1 ET_r sample values

$z_1(x_i)$ (David, 1977; Journel and Huijbregts, 1978).

$$z_1^*(x_0) = \sum_{i=1}^{n_1} \lambda_{1i} z_1(x_i) \quad [1]$$

Where: λ_{1i} = weight assigned to the experimental value of ET_r at sample point x_i .

The n_1 weights λ_{1i} account for the known spatial dependence expressed in the semivariogram and the geometric relationship among the sample points. Under the conditions of unbiasedness of the estimator and minimal kriging estimation error variance, a system of n_1+1 linear equations, the kriging system of equations, with n_1+1 unknowns was developed to solve for the n_1 weights λ_{1i} and a dummy variable, the Lagrange multiplier μ (David, 1977; Journel and Huijbregts, 1978; Cuenca and Amegee, 1987). The kriging estimation error variance, $\sigma_{OK}^2(x_0)$, also known as the kriging variance, was computed as

$$\sigma_{OK}^2(x_0) = \sum_{i=1}^{n_1} \lambda_{1i} \gamma_{11}(h_{i0}) + \mu \quad [2]$$

Where: $\gamma_{11}(h_{i0})$ = direct-semivariogram model value for distance h_{i0} which separates a sample point x_i from the point x_0 .

Similarly, in cokriging, the unknown value of ET_r at a point x_0 was estimated by a linear combination of n_1 ET_r sample values and $n_2 = n_1 + n_k$ sample values of elevation $z_2(x_j)$ (Journel and Huijbregts, 1978; Vieira et al., 1983).

$$z_1^*(x_0) = \sum_{i=1}^{n_1} \lambda_{1i} z_1(x_i) + \sum_{j=1}^{n_2} \lambda_{2j} z_2(x_j) \quad [3]$$

Where: λ_{2j} = weight assigned to the experimental value of elevation at sample point x_j .

Under the conditions of unbiasedness of the estimator and minimal cokriging estimation error variance, a system of

n_1+n_2+2 linear equations, the cokriging system of equations, was developed to solve for the n_1+n_2 weights and the Lagrange multipliers μ_1 and μ_2 (Journel and Huijbregts, 1978; Vieira et al., 1983). The cokriging estimation error variance, $\sigma_{CK}^2(x_0)$, also known as the cokriging variance, was computed as

$$\sigma_{CK}^2(x_0) = - \sum_{i=1}^{n_1} \lambda_{1i} \gamma_{11}(h_{i0}) + \sum_{j=1}^{n_2} \lambda_{2j} \gamma_{12}(h_{j0}) + \mu_1 \quad [4]$$

Where: $\gamma_{12}(h_{j0})$ = cross-semivariogram model value for distance h_{j0} which separates a sample point x_j from the point x_0 .

In all 44 study cases, both kriging and cokriging estimates were computed at a grid interval of approximately 5 km, at exactly the same points where elevation values were available. Kriging and cokriging variances were determined for each estimation point and the square roots of these variances computed. Maxima, minima and averages of the kriging and cokriging standard deviations were determined and compared for each case.

Mapping of ET_r estimates and errors

The commercial computer program SURFER v. 4.0 was used to map the kriged and cokriged annual ET_r estimates and their kriging and cokriging standard deviations. These maps allowed a graphical comparison of kriging and cokriging. The contour intervals of the maps were selected according to two criteria: 1) the chosen interval width was higher than the corresponding average kriging or cokriging standard deviations; and 2) a number of about 10 to 12 contour intervals was considered the maximum possible under the constraints imposed by the selected mapping scale. This second criteria was used to select appropriate contour intervals for the maps of kriging and cokriging standard deviations.

RESULTS AND DISCUSSION

Semivariogram modeling and validation

Direct-semivariograms for ET_r . In general, the experimental direct-semivariogram values progressively increased with distance and exhibited a more or less random fluctuation around a constant value beyond a certain distance (Figure 2). Due to the relatively high amount of scatter exhibited by the experimental semivariograms, no obvious theoretical models seemed to fit the sample values in a straightforward manner. At this point, the application of geostatistics becomes somewhat a subjective procedure where the experience, the knowledge and the biases of the modeler are factors to be considered. Fortunately, it has been indicated that the kriging and cokriging variances are robust to most errors likely to be made in semivariogram model selection and parameterization (Brooker, 1986). One of the most common semivariogram models used in hydrology is the spherical model. This model has previously been successfully applied to study the spatial variability of ET_r (Cuenca and Amegee, 1987; Nuss, 1989) and was therefore used for the same purpose in this study. No nested structures other than nugget effects were evident in the experimental semivariograms.

Table 2 lists the parameters of the different spherical models fit to the experimental semivariograms and the cross-validation statistics for each of the 44 study cases. All models showed adequate cross-validation statistics meeting the criteria outlined in Table 1. These cross-validation statistics were used as the main criteria to accept a particular model as adequate.

The nugget effect accounts for the variation of ET_r within a scale smaller than the spacing between weather stations at which local values of ET_r were available. The density of weather stations was different at each region which could explain some of the differences in the nugget effect between the regions. The nugget effect also accounts for the experimental error of ET_r at the weather stations. Recall that

the local values of ET_r used to compute the experimental semivariograms were estimates themselves obtained by applying the FAO-USDA Blaney-Criddle method. This method was chosen because of the similarity between the general climatic and aridity conditions of Oregon and those of Idaho, where the FAO-USDA Blaney-Criddle method was calibrated and tested for the months of April to October (Allen and Pruitt, 1986). However, there still exists some uncertainty about the actual performance of the method at each particular weather station site because of the local climatic and aridity conditions of each site for different periods during the year. As a consequence, it could be expected that errors in the local values of ET_r vary from region to region and from month to month.

It was therefore not surprising that there was evidence of a nugget effect in most of the experimental semivariograms. However, in some cases a nugget effect equal to zero was assumed based on the cross-validation statistics. Note that the nugget effect, in general, was higher for the warmer months of the year. This result was at least partially due to the fact that the variance of the ET_r values during those months was higher than during winter months (Martínez-Cob, 1990). In general, the nugget effects shown in Table 2 were lower than those reported by Nuss (1989) in a previous study of the application of geostatistics for evapotranspiration. Nuss (1989) performed the study for similar climatic regions in Oregon using three-year averages of local ET_r which probably led to a higher degree of uncertainty in the sample values of ET_r and, therefore, to higher nugget effects.

The ranges of the semivariogram models also showed some variation during the year (Table 2). During the warmer months, the ranges were shorter for region A and longer for regions B and D. Region C showed less variation in range than the other three regions. In the case of annual ET_r , the ranges were similar to those for the warmer months. Recall that ET_r rates during the warmer months are the highest and have the greatest influence on the annual ET_r rates. Ranges of regions A, B and C

were relatively similar while region D showed higher range values. Ranges shown in Table 2 were similar to those from Nuss (1989) with the exception of region A in which ranges were greater.

Direct-semivariograms for elevation. Table 3 lists the parameters of the fit isotropic direct-semivariogram models for elevation and the corresponding cross-validation statistics. With the exception of region B, models with nested structures were fit. Nugget effects were also evident in these models. The elevation semivariogram in region A was fit by a model with two nested structures, a gaussian structure with a range of 85 km and a spherical structure with a range of 125 km. The range of the gaussian structure was very similar to the one observed for the direct-semivariogram for annual ET_r . In regions C and D, the semivariogram model was made up of two nested structures, a spherical structure and a linear structure. Note the small range of the spherical structures, 30 and 60 km, for regions C and D, respectively, compared with the range of the direct-semivariograms for ET_r within the two regions. For region B, the semivariogram was fit by a model with a spherical structure with a particularly large range of 175 km.

Cross-semivariograms. The experimental cross-semivariograms also showed a high amount of scatter and, in general, no obvious theoretical models were evident (Figure 2). However, spherical models were fit to the experimental cross-semivariograms because spherical structures were fit to both direct-semivariograms and, under the assumptions of the linear model of coregionalization, any structure present in a cross-semivariogram must also appear in both direct-semivariograms (Journel and Huijbregts, 1978). In region B, the modeling of cross-semivariograms was somewhat more difficult because the experimental cross-semivariogram values were higher than the absolute values of the PDC curve for some of the distances computed. In this case, the experimental values meeting the positive definite condition were considered more representative of the underlying theoretical cross-

semivariogram. Validity of the selected models and parameters was based mainly on the cross-validation statistics.

Table 4 lists the parameters of the model semivariograms and the cross-validation statistics for all 44 study cases. There was no clear evidence of nugget effects. These were assumed equal to zero in all cases and this assumption was supported by the cross-validation statistics. In general, the ranges defined for the direct-semivariograms for ET_r seemed appropriate for the spherical models in the cross-semivariograms. However, in region B it was usually necessary to define larger ranges than those used for direct-semivariograms for ET_r because most of the cross-semivariogram experimental values meeting the positive definite condition were at distances close to or greater than the ranges of the direct-semivariograms for ET_r . Cross-validation results were used to support the selected ranges.

Kriging and Cokriging

Table 5 lists the maximum, minimum and average values of the kriged and cokriged estimates of ET_r and their percent differences for the four regions under study. In general, no differences between kriging and cokriging were noticed for the maxima of the estimated values, with the exception of region B where a slight difference was observed. Due to the inverse correlation between ET_r and elevation, maximum values of ET_r tended to occur in locations at lower elevation. Estimates of ET_r at those locations should be less affected by the cokriging procedure than estimates in locations at higher elevation, where differences between kriging and cokriging should be greater. The minima and averages of the estimated values were consistently smaller for cokriging than kriging in all regions. This decrease was particularly noticeable for the minima of the estimated values in region B, where a decrease of approximately 15 to 20 % was observed. In general, decreases in the average values were small and within the expected accuracy of the method used to compute the local estimates of ET_r .

Figures 3 and 4 show the contour maps of kriged and cokriged annual ET_r estimates, respectively. In general, the kriged contours were very smooth and followed roughly the main features of elevation. However, the cokriged contours followed these elevation changes much more closely. The kriged and cokriged contours were relatively similar in areas of low elevation, for example in the West and North areas of region A and the North area of region B (Figures 3 and 4). However, in areas of high elevation, the cokriged contours provided finer detail of the changes of ET_r as the elevation changes. Notice, for example, in region B the general trend of cokriged contours in the South area (Figure 4) which resembled closer the trend in elevation (Figure 1) while kriged contours did not follow it at all. Another example was in the East area of region A, close to the mountainous group observed in Figure 1. In general, the cokriged contours of monthly ET_r followed the same pattern as cokriged contours of annual ET_r (Martínez-Cob, 1990). In all cases ET_r decreased as elevation increased as expected due to the negative correlation between the two variables.

Table 6 lists the maximum, minimum and average values of the kriging and cokriging standard deviations and their percent differences for the four regions under study. In all regions, a consistent decrease in the maxima and averages of the estimation error standard deviations was noticed for cokriging in all study cases. No differences were observed for the minimum values. As discussed previously, the minimum estimation errors could be expected in locations at lower elevation where the influence of elevation was less significant and less differences should be expected between kriging and cokriging. The differences between kriging and cokriging standard deviations were larger for regions A and B, where higher correlation coefficients between the two analyzed variables were noticed. The highest decrease of the average estimation error standard deviation was observed for February (35 %) in region A, and April (30 %) in region B, while the lowest decrease was observed for October (15 %) in region A

and November (10 %) in region B. The decrease of average estimation error standard deviation for annual ET_r was 28 % for region A and 25 % for region B. In region C, the decrease of average estimation error standard deviation ranged from 13 % for March to 5 % for September, being 12 % for annual ET_r . In region D, the decrease of average estimation error standard deviation ranged from 12 % for June and annual ET_r to 7 % in October.

These improvements due to cokriging were relatively low compared to those observed in a similar study performed in Nevada with total annual precipitation and elevation (Hevesi et al., 1991). Recall that the experimental values of ET_r used in this project were themselves estimates. Thus, a higher experimental error may be expected in these values compared with precipitation which was actually measured by Hevesi et al. (1991).

Figures 5 and 6 show the contour maps of the kriging and cokriging standard deviations of annual ET_r , respectively. For regions A and B, there were important differences between kriging and cokriging. Note the dense contouring of the kriging standard deviations and the large decrease of the contours in the vicinity of the weather stations. In cokriging, the standard deviations were very uniform and lower over each region, except on the borders. The decrease of the estimation errors in the vicinity of the weather stations was not as large as for kriging. This was particularly evident in region B. Estimation errors increased at the borders for both kriging and cokriging, but the increases and the absolute values were higher using kriging.

In regions C and D, progressive increases in the estimation errors were observed for kriging as the estimation points moved away from the weather stations (Figure 5). In cokriging, this effect was also noticed but not as pronounced (Figure 6). The gradual increase of the estimation errors in the border region was very similar for kriging and cokriging although the maxima values were smaller for cokriging. It can be concluded that cokriging did not perform in regions C and D

as well as it did in regions A and B. The correlation coefficients between ET_r and elevation were higher in these latter two regions than in regions C and D (Martínez-Cob, 1990). This fact may have occurred simply because the spatial distribution of the weather stations was not completely random. Weather stations tend to be located close to populated areas and the population density in regions C and D is lower and more irregularly distributed. Likewise, the density of secondary data weather stations in these two regions was much lower than in regions A and B. Consequently, the values of the secondary weather parameters extrapolated to the primary data weather stations in regions C and D may not have adequately represented the general climatic conditions of those stations.

CONCLUSIONS

One of the important aspects of hydrology which has traditionally received little attention is topography (Burgess, 1986). This research showed that multivariate geostatistics can be a useful tool to predict changes in hydrological variables, such as evapotranspiration, as a function of altitude. More accurate estimates of ET_r were computed and contoured by application of the multivariate spatial variability of ET_r in conjunction with elevation using cokriging. The potential of a multivariate geostatistical approach to analyze the spatial variability of other hydrological variables, such as precipitation, as function of altitude has also been reported (Hevesi et al., 1991). The usefulness of multivariate geostatistics for ET_r analysis is dependent upon the different climatic region analyzed. In regions with a high statistical correlation between available data and elevation, the benefits will be maximized. In other regions, the use of a multivariate geostatistical approach may be too costly due to the high computational requirements and low potential for improvement in accuracy of the ET_r estimates.

The results of this project indicated additional potential applications of multivariate geostatistics. Errors associated with the estimation of ET_r using univariate

geostatistics may be used to optimize sample network design. Zones within a region in which more sampling sites (i.e. weather stations) are needed to further reduce the estimation errors can be identified. This research showed the improvement in the estimation errors using a multivariate geostatistical approach. The benefit of this approach in economic terms is evident compared with univariate geostatistics. The cost of using elevation data, which is readily available in digital form for most of the United States, is almost negligible compared with the costs of the installation, maintenance and operation of new weather stations. Because the most important decrease in the estimation errors due to multivariate geostatistics was observed for the maximum estimation error standard deviation values, this approach may allow a better identification of the locations where the installation of new weather stations is most critical.

Evapotranspiration is an important component of the annual hydrological balance on a continental scale. The long-term estimates of evapotranspiration computed in this research could be used as input in the hydrologic balance equation for various long-term regional studies, such as management of water resources and environmental assessments. Because of the reduced errors in the cokriged estimates of ET_r , an improvement in the uncertainty involved in this type of study is to be expected. The importance of the reduced errors in ET_r is more clearly perceived when the additive nature of errors in successive years is considered. Better and more accurate predictions of hydrological events, such as runoff, could result from this type of analysis.

It is known that the phenomenon of evapotranspiration affects the thermodynamic and dynamic state of the atmosphere (André et al., 1986). General circulation models (GCMs) of the atmosphere have made possible an initial examination of these effects. However, the parameterization of evapotranspiration in the present GCM models is in general too simple and further improvements are required (André et al., 1986). Multivariate geostatistics can be applied with meteorological and elevation

data available on the global scale. This approach could allow a better understanding of the spatial variability of evapotranspiration as affected by elevation. The more accurate cokriged estimates of evapotranspiration offer the potential to allow a spatial integration of evapotranspiration to GCM grids.

Finally, several specific recommendations for future research can be made from the results of this project.

- 1) One of the problems to develop a valid and adequate spatial variability model of ET_r was the error inherent in the local estimates of ET_r computed by using the FAO-USA Blaney-Criddle method. The uncertainty of this method should be included in the modeling of semivariograms for ET_r and cross-semivariograms. Further research should be focused on this problem.
- 2) The accuracy of the cokriged estimates of ET_r at the edges of the different climatic regions was relatively questionable. The problem of the border effect has not been correctly addressed. It would be beneficial to develop a procedure which would systematically correct this problem. One alternative could be the use of locations from other regions situated in the neighborhood of the region being studied.
- 3) The direct-semivariograms for ET_r modeled and cross-validated in this project were developed using long-term averages of ET_r . The feasibility of applying these models over shorter time should be tested. Previous work by Nuss (1989) for a three year period showed a high variability of semivariogram model parameters for successive years.
- 4) One of the main disadvantages of cokriging was the high computational efforts required. Other interpolation methods which combine geostatistical analysis with linear regression techniques should be tested and compared with cokriging. Assuming the cokriging estimates are the most accurate, this comparison could be used to evaluate the relative accuracy of simpler regression techniques compared

to cokriging. The result may point towards techniques which could reduce the cost of computer time in a routine procedure to contour ET_r at a regional scale.

- 5) The study of the spatial variability of several meteorological parameters, including relative humidity, wind speed, solar radiation and pan evaporation is recommended. The relative sparseness of present weather data bases preclude this research. The need to install additional weather stations which record parameters of this type is stressed. The inclusion of the spatial variability and correlation of these parameters with ET_r in a geostatistical analysis could improve the accuracy of the estimates of ET_r .

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TABLE 1. Cross-validation criteria for: I) the direct-semivariograms for ET_r and the cross-semivariograms; and II) direct-semivariograms for elevation.

	Reg	Sample size	AKE	MSE	SMSE
Criteria I	A	57	0	$MSE < s_{sp}^2$ ¹	1±0.3746
	B	41	0	$MSE < s_{sp}^2$	1±0.4417
	C	52	0	$MSE < s_{sp}^2$	1±0.3922
	D	49	0	$MSE < s_{sp}^2$	1±0.4041
Criteria II	A	1417	0	$MSE < 220037$ ²	1±0.0751
	B	1545	0	$MSE < 148278$	1±0.0720
	C	3233	0	$MSE < 52537$	1±0.0497
	D	2574	0	$MSE < 105775$	1±0.0557

¹ s_{sp}^2 represents the sample variance of ET_r values for each of the 44 study cases.

² These values are the sample variances (m^2) of elevation in each region.

TABLE 2. Spherical models for direct-semivariograms for ET_r and cross-validation statistics.

Reg	Month	Nugget ¹ (mm ² d ⁻²)	Sill ¹ (mm ² d ⁻²)	Range (km)	AKE ² (mm d ⁻¹)	MSE ¹ (mm ² d ⁻²)	Sample var ¹ (mm ² d ⁻²)	SMSE ¹ (mm ² d ⁻²)
A	Feb	0.000	0.034	100	0.005	0.008	0.027	0.988
	Mar	0.001	0.077	100	0.004	0.024	0.070	0.972
	Apr	0.005	0.136	80	0.005	0.064	0.137	0.992
	May	0.005	0.145	80	0.004	0.070	0.158	0.992
	Jun	0.015	0.109	80	0.002	0.068	0.117	0.976
	Jul	0.015	0.120	85	-0.003	0.065	0.134	0.976
	Aug	0.016	0.089	70	-0.004	0.063	0.104	0.988
	Sep	0.010	0.065	80	0.001	0.041	0.073	0.988
	Oct	0.008	0.028	105	0.003	0.020	0.036	0.984
	Nov	0.001	0.013	115	0.003	0.005	0.014	0.998
	Annu	200	6700	80	0.7	3230	6810	0.988
B	Feb	0.005	0.021	65	-0.003	0.019	0.024	0.990
	Mar	0.007	0.066	75	-0.009	0.048	0.069	1.032
	Apr	0.010	0.205	80	-0.014	0.118	0.213	1.024
	May	0.018	0.301	100	-0.011	0.148	0.356	1.022
	Jun	0.065	0.325	95	-0.012	0.217	0.406	0.978
	Jul	0.040	0.334	100	-0.013	0.176	0.373	0.990
	Aug	0.048	0.306	105	-0.009	0.162	0.365	0.914
	Sep	0.025	0.114	100	-0.012	0.073	0.146	0.960
	Oct	0.006	0.053	80	-0.014	0.036	0.059	1.030
	Nov	0.002	0.010	80	-0.007	0.008	0.014	1.030
	Annu	2020	12280	105	-2.2	7380	13280	1.012
C	Feb	0.001	0.028	95	-0.002	0.013	0.027	1.000
	Mar	0.001	0.044	90	-0.002	0.024	0.043	1.014
	Apr	0.019	0.088	100	0.000	0.065	0.107	1.008
	May	0.010	0.111	100	0.001	0.062	0.127	0.990
	Jun	0.005	0.132	100	-0.005	0.062	0.138	0.962
	Jul	0.008	0.152	105	0.004	0.065	0.166	0.980
	Aug	0.010	0.121	100	0.002	0.059	0.131	1.012
	Sep	0.004	0.088	105	0.004	0.032	0.094	1.010
	Oct	0.001	0.048	115	0.004	0.015	0.049	0.931
	Nov	0.001	0.011	115	0.000	0.006	0.012	1.018
	Annu	70	6250	100	0.8	2390	6380	0.931
D	Feb	0.000	0.037	85	0.013	0.018	0.037	0.984
	Mar	0.009	0.100	115	0.008	0.052	0.111	0.941
	Apr	0.019	0.294	125	0.021	0.119	0.313	0.943
	May	0.003	0.405	135	0.018	0.122	0.391	0.925
	Jun	0.000	0.590	160	0.014	0.138	0.590	0.780
	Jul	0.024	0.466	135	0.017	0.176	0.461	0.982
	Aug	0.023	0.257	120	0.014	0.138	0.247	1.111
	Sep	0.038	0.159	130	0.015	0.098	0.180	0.958
	Oct	0.019	0.115	140	0.015	0.059	0.145	0.970
	Nov	0.003	0.023	90	0.011	0.014	0.027	0.962
	Annu	1000	18400	135	4.5	7040	18120	0.947

¹ Annual ET_r , mm²

² Annual ET_r , mm.

TABLE 3. Models of direct-semivariograms for elevation and cross-validation statistics.

Reg	Nugget (m ²)	Gaussian		Spherical		Linear	AKE (m)	MSE (m ²)	Sample var (m ²)	SMSE
		Sill (m ²)	Range (km)	Sill (m ²)	Range (km)	Slope (m ² km ⁻¹)				
A	20000	200000	85	89000	125		0.73	26000	220000	0.978
B	8500			197500	175		0.14	15600	148300	0.936
C	1900			35300	30	77	0.21	9300	52500	0.973
D	15000			75500	60	245	-0.33	24900	105800	0.976

TABLE 4. Spherical models for cross-semivariograms and cross-validation statistics.

Reg	Month	Nugget ¹ (m mm d ⁻¹)	Sill ¹ (m mm d ⁻¹)	Range (km)	AKF ² (mm d ⁻¹)	MSE ³ (mm ² d ⁻²)	Sample var ³ (mm ² d ⁻²)	SMSE
A	Feb	0.000	-50.4	100	0.007	0.003	0.027	0.999
	Mar	0.000	-72.4	100	0.008	0.010	0.070	1.002
	Apr	0.000	-84.6	80	0.011	0.030	0.137	1.027
	May	0.000	-90.1	80	0.010	0.031	0.158	1.053
	Jun	0.000	-86.1	80	0.008	0.030	0.117	0.992
	Jul	0.000	-85.0	85	0.007	0.034	0.134	0.967
	Aug	0.000	-68.9	70	0.007	0.035	0.104	1.072
	Sep	0.000	-63.9	80	0.006	0.022	0.073	1.056
	Oct	0.000	-48.5	105	0.006	0.012	0.036	0.968
	Nov	0.000	-31.8	115	0.004	0.003	0.014	0.934
	Annu	0.000	-19400	80	1.9	1380	6810	1.052
B	Feb	0.000	-34.5	65	-0.029	0.009	0.024	1.030
	Mar	0.000	-76.5	90	-0.052	0.019	0.069	0.978
	Apr	0.000	-143.5	100	-0.085	0.048	0.213	0.979
	May	0.000	-192.0	120	-0.083	0.060	0.356	0.947
	Jun	0.000	-205.0	115	-0.110	0.104	0.406	0.921
	Jul	0.000	-193.0	120	-0.084	0.108	0.373	1.067
	Aug	0.000	-178.9	125	-0.071	0.127	0.365	1.125
	Sep	0.000	-125.5	125	-0.063	0.047	0.146	1.088
	Oct	0.000	-63.5	90	-0.047	0.017	0.059	0.940
	Nov	0.000	-17.6	80	-0.016	0.004	0.014	0.680
	Annu	0.000	-37900	115	-20.2	3450	13280	0.969
C	Feb	0.000	-15.8	95	-0.034	0.013	0.027	1.161
	Mar	0.000	-24.7	90	-0.059	0.020	0.043	1.107
	Apr	0.000	-39.2	100	-0.116	0.057	0.107	1.186
	May	0.000	-40.9	100	-0.101	0.053	0.127	1.119
	Jun	0.000	-40.6	100	-0.094	0.057	0.138	1.137
	Jul	0.000	-42.9	105	-0.086	0.060	0.166	1.101
	Aug	0.000	-31.8	100	-0.064	0.060	0.131	1.133
	Sep	0.000	-26.2	105	-0.045	0.032	0.094	1.111
	Oct	0.000	-21.0	115	-0.033	0.014	0.049	1.000
	Nov	0.000	-10.4	115	-0.020	0.006	0.012	1.110
	Annu	0.000	-9340	100	-20.0	2270	6380	1.170
D	Feb	0.000	-32.6	85	-0.009	0.013	0.037	1.063
	Mar	0.000	-69.3	115	-0.036	0.037	0.111	0.939
	Apr	0.000	-116.5	125	-0.044	0.086	0.313	0.929
	May	0.000	-132.0	135	-0.040	0.088	0.391	0.966
	Jun	0.000	-178.5	160	-0.052	0.100	0.590	0.838
	Jul	0.000	-148.0	135	-0.059	0.126	0.461	0.970
	Aug	0.000	-103.0	120	-0.049	0.102	0.247	1.084
	Sep	0.000	-103.5	130	-0.070	0.070	0.180	0.916
	Oct	0.000	-70.5	140	-0.026	0.045	0.145	0.904
	Nov	0.000	-26.0	90	-0.010	0.011	0.027	0.942
	Annu	0.000	-31550	135	-12.5	4870	18120	0.940

¹ Annual ET_r, m mm² ² Annual ET_r, mm ³ Annual ET_r, mm².

TABLE 5. Comparison of kriged and cokriged ET_r estimates.

Reg	Month	Maximum			Minimum			Average		
		Krig ¹ (mm d ⁻¹)	Cokg ¹ (mm d ⁻¹)	Diff (%)	Krig ¹ (mm d ⁻¹)	Cokg ¹ (mm d ⁻¹)	Diff (%)	Krig ¹ (mm d ⁻¹)	Cokg ¹ (mm d ⁻¹)	Diff (%)
A	Feb	1.1	1.1	-2.5	0.2	0.0	-100.1	0.7	0.7	-10.0
	Mar	2.0	2.0	-1.1	0.6	0.4	-35.2	1.5	1.4	-7.3
	Apr	3.4	3.4	-0.9	1.5	1.3	-14.9	2.8	2.6	-5.8
	May	4.6	4.5	-0.6	2.6	2.4	-7.6	3.9	3.7	-4.5
	Jun	5.1	5.1	0.7	3.7	3.3	-9.3	4.6	4.5	-3.6
	Jul	6.0	6.0	-0.4	4.5	4.2	-7.2	5.3	5.1	-2.8
	Aug	5.0	5.0	-0.7	3.6	3.3	-9.4	4.4	4.3	-3.2
	Sep	3.8	3.8	1.0	2.6	2.4	-9.6	3.4	3.3	-3.5
	Oct	2.3	2.2	-1.1	1.5	1.3	-11.3	2.0	2.0	-3.3
	Nov	0.8	0.7	-2.8	0.2	0.1	-51.0	0.6	0.5	-7.2
	Annu	1031	1021	-1.0	621	571	-8.1	904	867	-4.1
B	Feb	0.8	0.8	-2.7	0.1	0.0	-167.4	0.6	0.5	-12.6
	Mar	2.1	2.0	-3.5	0.7	0.5	-31.7	1.6	1.4	-8.0
	Apr	4.3	4.2	-2.0	2.0	1.7	-15.6	3.2	3.0	-5.8
	May	6.1	5.9	-2.8	3.3	2.9	-13.0	4.5	4.3	-4.4
	Jun	7.0	6.7	-4.5	4.2	3.3	-20.9	5.5	5.2	-4.9
	Jul	7.7	7.6	-2.0	5.6	4.7	-16.0	6.4	6.2	-3.2
	Aug	6.9	6.7	-2.9	4.6	3.6	-20.5	5.3	5.2	-3.4
	Sep	4.6	4.5	-2.3	3.4	2.8	-17.0	3.8	3.7	-3.7
	Oct	2.7	2.7	-2.1	1.5	1.3	-13.7	2.3	2.2	-4.3
	Nov	0.7	0.7	-0.5	0.2	0.1	-36.9	0.5	0.5	-5.3
	Annu	1299	1245	-4.2	808	650	-19.6	1032	983	-4.7
C	Feb	0.7	0.8	1.9	0.1	0.0	-48.1	0.4	0.3	-13.9
	Mar	1.5	1.5	0.5	0.5	0.5	-6.9	1.1	1.0	-8.8
	Apr	3.0	3.0	-1.0	1.7	1.5	-12.0	2.4	2.3	-7.5
	May	4.2	4.2	-0.3	2.6	2.5	-3.7	3.6	3.5	-4.4
	Jun	5.3	5.3	0.4	3.6	3.5	-2.4	4.6	4.5	-3.2
	Jul	6.2	6.2	0.5	4.8	4.4	-6.7	5.4	5.3	-2.6
	Aug	5.0	5.0	-0.3	3.7	3.5	-5.0	4.4	4.3	-2.4
	Sep	3.9	3.9	-0.4	2.7	2.6	-5.6	3.2	3.2	-2.4
	Oct	2.5	2.5	0.6	1.6	1.5	-7.6	2.1	2.0	-2.9
	Nov	0.7	0.7	0.9	0.3	0.2	-18.7	0.4	0.4	-7.6
	Annu	999	1003	0.4	662	622	-6.1	846	814	-3.9
D	Feb	0.7	0.7	0.5	0.0	0.0	-426.6	0.3	0.3	-13.9
	Mar	1.8	1.8	0.5	0.6	0.3	-38.4	1.2	1.1	-7.1
	Apr	4.1	4.1	0.3	1.9	1.6	-15.1	2.9	2.7	-4.5
	May	5.5	5.5	0.3	3.1	2.7	-12.9	4.0	3.9	-3.1
	Jun	6.8	6.9	0.3	3.9	3.5	-10.7	5.0	4.8	-3.9
	Jul	7.6	7.6	-0.1	5.0	4.6	-8.9	6.1	5.9	-2.5
	Aug	6.0	6.0	0.0	4.0	3.7	-6.2	5.0	4.8	-2.4
	Sep	4.4	4.4	0.2	3.0	2.6	-11.3	3.6	3.5	-3.7
	Oct	2.8	2.8	0.0	1.6	1.4	-9.5	2.2	2.1	-3.5
	Nov	0.7	0.7	-0.0	0.1	0.0	-79.8	0.4	0.4	-9.6
	Annu	1208	1211	0.3	718	624	-13.1	936	904	-3.5

¹ Annual ET_r , mm.

TABLE 6. Comparison of kriging and cokriging standard deviations.

Reg	Month	Maximum			Minimum			Average		
		Krig ¹ (mm d ⁻¹)	Cokg ¹ (mm d ⁻¹)	Diff (%)	Krig ¹ (mm d ⁻¹)	Cokg ¹ (mm d ⁻¹)	Diff (%)	Krig ¹ (mm d ⁻¹)	Cokg ¹ (mm d ⁻¹)	Diff (%)
A	Feb	0.18	0.13	-26.0	0.02	0.02	-1.8	0.09	0.06	-34.7
	Mar	0.27	0.21	-22.5	0.05	0.05	-1.1	0.14	0.10	-28.4
	Apr	0.40	0.32	-20.2	0.10	0.10	-1.3	0.22	0.17	-25.5
	May	0.41	0.32	-21.8	0.10	0.10	-1.5	0.23	0.17	-27.8
	Jun	0.38	0.29	-23.3	0.15	0.14	-6.3	0.23	0.17	-26.1
	Jul	0.39	0.31	-19.2	0.15	0.15	-3.7	0.24	0.19	-20.6
	Aug	0.37	0.30	-18.3	0.16	0.15	-5.1	0.23	0.18	-22.1
	Sep	0.30	0.23	-20.7	0.12	0.12	-5.3	0.18	0.14	-22.5
	Oct	0.19	0.16	-17.5	0.10	0.10	-5.1	0.13	0.11	-15.1
	Nov	0.11	0.09	-19.5	0.04	0.04	-2.6	0.07	0.05	-20.1
	Annu	88	69	-22.1	20	20	-1.4	49	35	-28.5
B	Feb	0.19	0.14	-27.9	0.09	0.08	-7.2	0.13	0.10	-26.8
	Mar	0.31	0.20	-36.1	0.12	0.11	-6.2	0.19	0.14	-28.2
	Apr	0.52	0.32	-38.5	0.15	0.14	-4.6	0.30	0.21	-30.4
	May	0.58	0.35	-40.3	0.19	0.18	-6.8	0.34	0.24	-29.5
	Jun	0.67	0.41	-38.4	0.32	0.30	-6.7	0.44	0.33	-24.4
	Jul	0.64	0.43	-32.8	0.26	0.25	-5.2	0.39	0.31	-21.9
	Aug	0.61	0.44	-27.6	0.28	0.27	-4.2	0.39	0.32	-17.4
	Sep	0.39	0.25	-35.4	0.20	0.18	-5.8	0.26	0.21	-21.1
	Oct	0.27	0.19	-30.8	0.11	0.10	-5.3	0.17	0.13	-24.0
	Nov	0.12	0.11	-12.3	0.06	0.06	-2.1	0.08	0.07	-9.6
	Annu	123	77	-38.0	57	53	-6.8	79	59	-25.3
C	Feb	0.19	0.17	-10.5	0.05	0.04	-0.4	0.11	0.10	-6.8
	Mar	0.25	0.21	-15.1	0.05	0.05	-0.7	0.14	0.12	-12.6
	Apr	0.37	0.30	-18.2	0.17	0.17	-1.2	0.24	0.21	-12.4
	May	0.39	0.32	-17.3	0.13	0.13	-0.8	0.24	0.21	-11.4
	Jun	0.41	0.35	-14.7	0.10	0.10	-0.6	0.24	0.21	-9.6
	Jul	0.44	0.38	-13.6	0.12	0.12	-0.6	0.26	0.23	-8.5
	Aug	0.40	0.37	-9.1	0.13	0.13	-0.4	0.24	0.23	-5.5
	Sep	0.33	0.30	-8.5	0.09	0.09	-0.3	0.19	0.18	-5.1
	Oct	0.23	0.21	-9.7	0.05	0.05	-0.4	0.13	0.12	-5.8
	Nov	0.12	0.11	-9.7	0.04	0.04	-0.4	0.07	0.07	-5.5
	Annu	87	73	-17.1	14	14	-0.8	49	43	-11.8
D	Feb	0.27	0.23	-14.5	0.03	0.03	-1.3	0.13	0.12	-11.0
	Mar	0.39	0.30	-24.9	0.13	0.13	-1.6	0.22	0.19	-11.2
	Apr	0.66	0.50	-23.3	0.19	0.19	-1.4	0.34	0.31	-10.4
	May	0.73	0.57	-21.6	0.10	0.10	-0.8	0.35	0.31	-10.8
	Jun	0.83	0.62	-24.9	0.08	0.08	-1.3	0.38	0.33	-12.2
	Jul	0.80	0.62	-22.9	0.22	0.22	-1.4	0.41	0.37	-10.1
	Aug	0.63	0.50	-20.5	0.20	0.20	-1.2	0.34	0.31	-9.0
	Sep	0.52	0.36	-31.0	0.24	0.23	-1.9	0.31	0.28	-11.2
	Oct	0.42	0.34	-18.3	0.17	0.17	-1.0	0.24	0.22	-6.7
	Nov	0.23	0.20	-12.9	0.07	0.07	-1.2	0.12	0.11	-7.8
	Annu	160	116	-27.1	44	44	-1.6	82	72	-11.8

¹ Annual ET_r, mm.

FIGURE 1. Contour map of elevation, m, of the four climatic regions of Oregon under study: A) Willamette Valley; B) North Central; C) South Central; D) East.

A

B

FIGURE 2. Model semivariograms: A) Direct-semivariogram for annual ET, in region C; B) Cross-semivariogram for annual ET, and elevation in region D.

FIGURE 3. Contour map of kriged estimates of annual ET_r , mm.

FIGURE 4. Contour map of cokriged estimates of annual ET_r , mm.

FIGURE 5. Contour map of kriging standard deviation for annual ET_r , mm.

FIGURE 6. Contour map of cokriging standard deviation for annual ET_r , mm.