ESTIMATION OF MEAN ANNUAL PRECIPITATION AS AFFECTED BY ELEVATION USING MULTIVARIATE GEOSTATISTICS

by

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ABSTRACT

This paper presents the results of the interpolation of annual precipitation over a regular grid performed in Aragón (Spain). The main objective was the quantification of the improvement in estimation precision by including elevation in the interpolation and by using base 10 logarithms of both annual precipitation and elevation versus the original values.

Long-term annual precipitation (APRE) was available at 182 weather stations. Elevation above sea level (ELEV) was available at those stations and at 1913 additional points over a regular 5 km grid. The spatial variability of APRE, ELEV

and their base 10 logarithms (LAPRE and LELEV, respectively), and the spatial correlation between APRE and ELEV, APRE and LELEV, LAPRE and ELEV, and LAPRE and LELEV were described by gaussian direct- and cross-semivariogram models with nugget effects.

Geostatistical interpolation methods, ordinary kriging and cokriging, were used to estimate APRE and LAPRE at the 1913 additional elevation points. Estimates of LAPRE were transformed back to APRE values. Cokriging estimates were in general higher than kriging ones, mainly at points of high elevation. The average percent difference among cokriging and kriging estimates was 9 to 12 %. Cokriging estimates obtained with the different sample data sets were in general terms similar. However, at points of high elevation, cokriging with ELEV as the auxiliary variable seemed to overestimate annual precipitation.

Estimation error standard deviations (EESD) also were computed in each interpolation point. For all points, the EESD obtained using LAPRE values were lower than those obtained using APRE values, being the average percent differences of -38 to -42 %. Likewise, for all interpolation points, cokriging EESD were lower than kriging ones. Using LAPRE and LELEV values, the average percent difference among cokriging and kriging EESD was -11.0 %, with minimum and maximum percent differences of -6.7 and -35.8 %, respectively.

Keywords: Interpolation Precision Cokriging Precipitation Elevation Geostatistics

INTRODUCTION

The appropriate management of agricultural and water resources demands a good knowledge of the spatial distribution of precipitation, one of the key variables for quantification and modeling of the hydrological balance at regional scales. Frequently, precipitation values are available at a number of weather stations and estimates in other areas are obtained by interpolation of those values.

Most of the interpolation techniques commonly used give arbitrary weights to the local values. Likewise, they usually do not provide any indication of the precision of the results (Delhomme, 1978). Geostatistics allows the modeling of the spatial variability of a variable based on the correlation between neighboring measurements. Geostatistics applies this modeled spatial variability together with spatial interpolation techniques such as ordinary kriging, to estimate that variable at locations where no measurements are available (Journel and Huijbregts, 1978). The method also quantifies the precision of the estimation (Delhomme, 1978). Ordinary kriging has previously been applied to the spatial interpolation of precipitation (Tabios and Salas, 1985; Beek, 1991).

Precipitation tends to increase with elevation above sea level. Weather stations usually are concentrated in areas with low elevations and ordinary kriging may thus underestimate the regional precipitation (Phillips et al., 1992). Previous attempts to solve this situation include those of Chua and Bras (1982) and Dingman et al. (1988). These authors used the method known as detrended kriging in which simple linear regressions of precipitation on elevation were computed, the spatial variability of the regression residuals was analyzed and modeled, and kriging of the regression residuals was performed. Ordinary cokriging is a multivariate geostatistical method which uses a second correlated auxiliary variable, such as elevation, to aid in the estimation of the primary variable, such as precipitation (Hevesi et al., 1992a, 1992b; Phillips et al., 1992). Ordinary cokriging is expected to reduce the estimation error variance if the auxiliary variable is highly correlated with the primary variable and is oversampled compared with this one, the magnitude of this reduction also depending on the data's spatial configuration (David, 1977; Hoeksema et al., 1989).

Geostatistical interpolation methods lead to optimum estimators when the sample values are normally distributed (Samper and Carrera, 1990). In the case of skewed distributions, it may be very convenient the transformation of the original sample values such that the transformed values approach a normal distribution. It has been argued that transformation to normality prior to geostatistical analysis results in a nonlinear function of the original data and then (co)kriging estimates may not be obtained with minimum estimation variance and without bias (Trangmar et al., 1985).

This paper presents the spatial analysis and modeling of long-term mean annual precipitation (APRE) performed in Aragón, Spain, using a multivariate geostatistical approach. The spatial correlation of APRE with elevation above sea level (ELEV) also was analyzed and modeled. Cross-validation was used for selection and validation of appropriate semivariogram models. The main objective was the interpolation of mean annual precipitation over a regular 5 km grid and the quantification of the improvement in estimation precision by including elevation in the interpolation. In this study, the sample values of APRE and ELEV approached a log-normal distribution. Therefore, the differences in estimation results obtained using the original values of these two variables versus their base 10 logarithms were compared to see whether the use of log-transformed sample values could improve the estimation precision.

MATERIAL AND METHODS

General description of the study area (Aragón)

The region of Aragón is located in the north east of Spain (Figure 1), covering an area of approximately 47,000 km^2. Aragón has three main landscape units (Figure 2): (a) the Pyrenees Range to the north, being Aragón where it attains the highest elevations (Aneto, 3408 m) and width (around 100 km);

(b) the Iberian Range, a mountainous chain stretching from northwest to southeast, less massive and continuous than the Pyrenees, with elevations not exceeding 2000 m, with a few exceptions: Moncayo (2316 m), Gúdar (2024 m) and Javalambre (2020 m); and (c) the Ebro River Depression to the centre, a plain consisting of a series of platforms and valleys, with elevations ranging from 200 to 800 m.

In the Ebro River Depression, the climate is continental mediterranean. The center of the Depression is markedly arid, with an average annual precipitation of 420 mm, but minimum values of 300 mm in some locations, and a large seasonal temperature variation: annual means of 15 °C and a mean annual oscillation of approximately 20 °C. The precipitation increases towards the mountainous ranges with an average annual precipitation of 1300 mm at the Pyrenees. However, in the Iberian Range, only the highest elevation locations receive 800 mm. The mean annual temperature at elevations higher than 1000 m is less than 10 °C and the mean annual oscillation is approximately 15 °C. Finally, the dominant wind is the so-called *cierzo*, whose direction is WNW and which is channelled along the Depression.

Description of the precipitation and elevation data bases

Long-term averages of monthly precipitation (MPRE, mm) were available at 182 precipitation weather stations. Length of meteorological records was 10-20 years for most weather stations although it was up to 50 years for some of the stations (Faci and Martínez-Cob, 1991). The 12 MPRE values were summed up to obtain long-term mean values of total annual precipitation (APRE, mm). Elevation (ELEV) was available at the weather stations and at 1913 additional sample points on a 5 km grid. These values were obtained from the 1:100000 maps of the Spanish Army Geographical Service.

Histogram and normal probability plots indicated that the values of APRE and ELEV were lognormally distributed. The fit of the histograms to a normal distribution was improved by the transformations LAPRE = 1000 [log(APRE)], and LELEV = 1000 [log)ELEV)], respectively, where *log* stands for the base 10 logarithm. Then, in this study four sets of sample values were available: APRE, LAPRE, ELEV and LELEV.

The following statistics were computed for a preliminary statistical analysis of the data values: mean, median, minimum, maximum, variance, coefficient of variation and standardized skewness. Likewise, simple linear regressions of both APRE and LAPRE on both ELEV and LELEV were calculated.

Geostatistical analyses

Semivariograms are the geostatistical tools which describe the spatial variability of the variables of interest and their spatial correlation. The first step required to model semivariograms is the computation of sample direct- and cross-semivariograms (David, 1977; Journel and Huijbregts, 1978; Hevesi et al., 1992a). Isotropic sample direct-semivariograms were computed for APRE, LAPRE, ELEV and LELEV. Isotropic sample cross-semivariograms were computed for APRE-ELEV, APRE-LELEV, LAPRE-ELEV and LAPRE-LELEV.

Visual inspection of sample semivariograms indicated that a gaussian semivariogram model might be appropriate for direct- and cross-semivariograms. The gaussian model has been described elsewhere (Delhomme, 1978; Journel and Huijbregts, 1978). Model parameters (nugget effect, sill and range) were estimated visually. Cross-validation 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 removed from the primary variable data set, and kriging or cokriging were used to estimate the value of the deleted sample. The estimation was done using the remaining samples and the selected semivariogram model and parameters. This procedure was repeated for all samples. Differences between estimated and sample values were summarized using the cross-validation statistics (Hevesi et al., 1992a): percent average estimation error (PAEE), relative mean-square error (RMSE), and standardized mean-square error (SMSE).

A model was considered to ensure unbiased estimates if the PAEE was close to zero. The RMSE also should be close to 0 and the model with minimum RMSE should be chosen (Cooper and Istok, 1988). The SMSE indicated the consistency of the calculated estimation error variances with the observed RMSE.

The estimation error variances were considered consistent if the SMSE was in the range $1\pm2\sqrt{2/n_i}$ (Delhomme, 1979) where n_i was the sample size. In this study, the SMSE should be within the following ranges: a) direct-semivariograms for APRE and LAPRE and cross-semivariograms, 1 ± 0.2097; and b) direct-semivariograms for ELEV and LELEV, 1 ± 0.0618.

Once, the semivariograms were modeled and cross-validated, they were used together with the geostatistical interpolation methods of ordinary kriging and cokriging to estimate APRE and LAPRE on a 5 km grid at the 1913 elevation sample points. The ordinary kriging and ordinary cokriging estimators are linear combinations of the sample values (Journel and Huijbregts, 1978; Hevesi et al., 1992a):

$$z_i^*(x_0) = \sum_{k=1}^{n_i} \lambda_{ik} z_i(x_k) + \sum_{l=1}^{n_j} \lambda_{jl} z_j(x_l) \tag{1}$$

where z_i^* is the estimate at point x_0, n_i and n_j are the number of sample points of z_i and z_j used in the estimation, and λ_{ik} and λ_{jl} are the associated weights. These weights account for the modeled spatial dependence expressed by the semivariograms and the geometric relationship among the sample points. The values $z_i(x_k)$ represent those of APRE or LAPRE at sample points x_k, while the values of $z_j(x_l)$ represent those of ELEV or LELEV at sample points x_l. For ordinary kriging, the weights λ_{jl} are 0 since only APRE or LAPRE contribute to the estimation process. Under the conditions of unbiasedness of the estimators and minimal ordinary kriging or ordinary cokriging estimation error variances, the model semivariograms were used within a system of equations to solve for the unknown weights (Journel and Huijbregts, 1978; Hevesi et al., 1992a).

The minimized estimation error variance at the unsampled location x_0, $\sigma^2_{CK}(x_0)$, was computed by the following expression (Journel and Huijbregts, 1978; Hevesi et al., 1992a):

$$\sigma^2_{CK}(x_0) = -\sum_{k=1}^{n_i} \lambda_{ik}\gamma_{ii}(h_{k0}) + \sum_{l=1}^{n_j} \lambda_{jl}\gamma_{ij}(h_{l0}) + \mu_i \qquad (2)$$

where $\gamma_{ii}(h_{k0})$ is the value of the direct-semivariogram for variable i for distance h_{k0} separating the sample point x_k from the point x_0, and $\gamma_{ij}(h_{l0})$ is the value of the cross-semivariogram for variables i and j for distance h_{l0} separating the sample point x_l from the point x_0. As in equation (1), the weights λ_{jl} are 0 for ordinary kriging.

Estimation error standard deviations (EESD) were computed as the square root of estimation error variances. Equations (1) and (2) were applied to obtain estimates and EESD of APRE for six different cases (Figure 3): KP, kriging of APRE; KLP, kriging of LAPRE; CKPE, cokriging of APRE and ELEV; CKPLE, cokriging of APRE and LELEV; CKLPE, cokriging of LAPRE and ELEV; and CKLPLE, cokriging of LAPRE and LELEV.

Estimates and EESD of LAPRE (cases KLP, CKLPE and CKLPLE) were transformed back to APRE values using the procedure described by Samper and Carrera (1990) and Hevesi et al. (1992b).

The geostatistical analysis were carried out with own software (computation of sample semivariograms) and software provided (cross-validation and interpolation) by Drs. J.A. Hevesi and A.L. Flint (Hydrologic Research Facility, U.S. Geological Survey, Mercury, Nevada).

RESULTS AND DISCUSSION

Table 1 lists some descriptive statistics of the sample values of APRE and LAPRE available at the weather stations and ELEV and LELEV available at the weather stations and 1913 additional sample points. These sample values showed an ample range of variation. Thus, APRE and ELEV varied from minimum values of 296.0 mm and 70.0 m, respectively, up to maximum values of 1976.0 mm and 2880.0 m, respectively. The coefficients of variation of APRE and ELEV were high (51 to 58 %), while those of LAPRE and LELEV were smaller (7.2 to 9.6 %). The standardized skewness of LAPRE and LELEV was reduced compared to that of APRE and ELEV. This suggests that the normal approximation was improved by applying the log transformation (Cochran, 1977).

Table 2 lists the results of simple linear regressions of both APRE and LAPRE on both ELEV and LELEV. The four linear regressions were significant and their correlation coefficients ranged from 0.68 to 0.74. These correlation coefficients indicate that an improvement of the estimation precision should be expected when using cokriging instead of kriging to interpolate annual precipitation using elevation as auxiliary variable.

Table 3 lists the parameters (nugget, sill and range) of the gaussian models fit to the different isotropic sample direct- and cross-semivariograms. The cross-validation statistics of the fit semivariogram models also are listed. The ranges of APRE and LAPRE were similar (132 and 136 km, respectively). Then, in Aragón, there was a spatial correlation among neighboring precipitation mesurements up to distances of approximately 130-140 km. Because of the spatial distribution of the sample points, this study was not appropriate to analyze spatial variability at small scales (microclimates). The nugget effects of the fit semivariogram models may reflect the spatial variability of APRE and LAPRE at these small scales (Journel and Huigbregts, 1978). The ELEV and LELEV had higher range values (165 and 156 km, respectively). These values indicate that the scale of spatial variatibility of ELEV and LELEV was slightly higher than that of APRE and LAPRE. Cross-validation statistics were used as the main criteria to validate a semivariogram model. The analysis and modeling of the spatial variability of annual precipitation and elevation and their spatial correlation is discussed in more detail by Martínez-Cob (1994).

Table 4 lists some descriptive statistics of the estimates and the EESD values of APRE obtained at the 1913 interpolation points using kriging and cokriging with the different sets of sample values. The averages of the kriging estimates (cases KP and KLP) were lower, 531-534 mm, than those of the cokriging estimates (cases CKPE, CKPLE, CKLPE and CKLPLE), 584-602 mm. The minima of the kriging estimates were in general higher, 323-327 mm, and the maxima were lower, 1639-1692 mm, than those of the cokriging estimates, 210-326 mm and 1672-2521 mm, respectively. The average elevation of the complete ELEV data set was higher than the average elevation of the weather stations (Table 1). Due to this fact and the positive correlation between annual precipitation and elevation (Table 2), it was expected that cokriging would lead to higher estimates. The coefficients of variation of the estimates were relatively similar in all cases, ranging from 43 to 48 %, except for cokriging estimates obtained using LAPRE and ELEV sample values (case CKLPE) for which the coefficient of variation was 57 %.

The kriging and cokriging EESD obtained using LAPRE sample values (cases KLP, CKLPE and CKLPLE) were significantly lower than those obtained using APRE sample values (cases KP, CKPE and CKPLE, Table 4). The averages of the EESD for these three last cases ranged from 94 to 111 mm while the averages of the EESD for cases KLP, CKLPE and CKLPLE ranged from 58 to 67 mm. These results suggest that the estimation precision was improved by the use of log-transformed values of annual precipitation. Likewise, cokriging EESD were lower than kriging ones. The highest differences among cokriging and kriging were observed for the maxima of the EESD. The maximum EESD were computed at points where few weather stations were available for the interpolation. Then, in these points the inclusion of the elevation values in the interpolation greatly improve the estimation precision. The coefficients of variation of the kriging EESD were about 28 %, and those of the cokriging EESD ranged from 16 to 22 %, depending whether ELEV or LELEV sample values were used.

For each interpolation point, it was computed the percent difference among the estimates obtained with the different sample data sets (Table 5). These results showed that the percent differences among kriging estimates (cases KP and KLP) were relatively small, with an average percent difference of -0.4 %. The averages of the percent differences among kriging and cokriging estimates obtained using APRE sample values (case KP versus cases CKPE and CKPLE) were 11-13 %, while the averages of the percent differences among kriging and cokriging estimates obtained using LAPRE sample values (case KLP versus cases CKLPE and CKLPLE) were around 9 %. Nevertheless, for some interpolation points of low elevation, cokriging estimates were lower than kriging ones (Figure 4). Likewise, the averages of the percent differences among the different cokriging estimates were small, less than 3 % (Table 5).

Therefore, in general terms the estimates were not affected by the use of the original or the log-transformed sample values. The differences among estimates mainly were due to the use of cokriging versus kriging because of the good correlation between annual precipitation and elevation. Nevertheless, there were some differences among cokriging estimates for extreme values of APRE. Figure 5 shows the cokriging estimates obtained for case CKPLE versus those obtained for case CKLPLE. It can be seen that for low or high values of APRE, estimates using LAPRE tend to be higher than those using APRE. Figure 5 also shows the cokriging estimates obtained for case CKLPE versus those obtained for case CKLPLE. The latter tend to be lower than the former for higher values of APRE. Similar behavior was observed when comparing the cokriging estimates obtained for case CKPE versus those obtained for case CKPLE. In other words, using ELEV as auxiliary variable instead of LELEV lead to higher estimates in the upper range of annual precipitation, i.e. at points of high elevation.

There were lower and higher elevation values at the 1913 additional sample points than those available at the weather stations (Table 1). This was the reason for cokriging estimates of APRE to be either lower or higher than the minimum or the maximum APRE sample values (Tables 1 and 4). Similar behavior was observed in previous geostatistical analysis of precipitation (Hevesi et al., 1992b; Phillips et al., 1992). It was particularly noticeable the case CKLPE for wich 24 estimates of APRE were higher than 2000 mm (the maximum APRE sample value was 1976 mm). These estimates were computed at sample locations with elevations well above the maximum elevation of the weather stations, 1660 mm (Table 1). It is possible that APRE was overestimated in case CKLPE for interpolation points with high elevation values.

Figure 6 shows maps of isolines of annual precipitation obtained by kriging of LAPRE and cokriging of LAPRE and LELEV. It can be seen that cokriging estimates followed more closely the topography of Aragón (Figure 2). This was more noticeable in the south of Aragón where less weather stations were available. The lowest estimates of annual precipitation (around 300-350 mm) were obtained in the central part of Aragón along the course of the Ebro River. The annual precipitation increased to the north reaching values of more of 1600 mm in the Pyrenees and to the south where it only reaches values of about 700 mm in the highest elevations.

Also, for each interpolation point, it was computed the percent difference among the EESD obtained with the different sample data sets (Table 6). The average of the percent differences among cokriging EESD for case CKLPE and cokriging EESD for case CKPE was -38 %, while the average of the percent differences among cokriging EESD for case CKLPLE and cokriging EESD for case CKPLE was -42 %. These results strongly suggest that the use of log-transformed values of annual precipitation has improved the estimation precision. If the original sample values are clearly lognormally distributed, smaller absolute values of the EESD should be expected when log-transformed sample values are used (Journel and Huigbregts, 1978). For all interpolation points, the cokriging EESD obtained using

LAPRE sample values were lower than those obtained using APRE sample values and the percent differences were very similar for all points (Table 6). By the other hand, the average of the percent differences among cokriging EESD for case CKLPLE and cokriging EESD for case CKLPE was 0.59 %, with a minimum percent difference of 3 % and a maximum difference of -16 %. These results suggest that in general terms the use of log-transformed values of annual precipitation lead to similar precision of the estimates regardless of the use of the original or the log-transformed values of elevation.

Cokriging improved the estimation precision as the percent differences among cokriging EESD and kriging EESD were negative for all interpolation points (Table 6). The averages of the percent differences among cokriging EESD and kriging EESD ranged from -7 to -14 % when using APRE sample values and from -11 to -12 % when using LAPRE sample values. These percent differences were as low as -2 % for some interpolation points and as high as -36 % for some other points. Again, these results suggest that in general terms the use of LAPRE sample values lead to smilar improvement of the estimation precision regardless of the use of ELEV or LELEV as the auxiliary variable.

The areas where more weather stations were available showed the lowest EESD for both kriging and cokriging, while the highest EESD were observed where few or none weather stations were available (Figure 7), where also the greatest percent differences among cokriging and kriging EESD were observed. It was noticeable the lack of weather stations in the south of Aragón. In this area, the EESD increased dramatically for both kriging and cokriging. This increase also was due to the border effect because no weather stations outside the limits of Aragón were used. However, this increase was less pronounced for cokriging as elevation sample values were used for the interpolation (Figure 7). The percent differences among cokriging EESD and kriging EESD were relatively similar for most of the interpolation points, with values about -7 to -15 %, but decreased dramatically for the southern interpolation points, reaching values up to -35 % (Figure 8).

The improvement due to cokriging was approximately of the same order of magnitude of that observed in previous multivariate geostatistical analyses of log annual precipitation using elevation (Hevesi et al., 1992a, 1992b) and log elevation (Phillips et al., 1992) as auxiliary variables, although the average of the percent differences obtained in this study was slightly lower. It should be kept in mind that the EESD reflect the uncertainty of the interpolation process, the model semivariograms represent the true spatial relationships and then, the ESSD do not reflect uncertainties in the fitting of these models. The improvement of the EESD due to cokriging is mainly due to the statistical correlation between the primary and the auxiliary variables and to the spatial configuration of the sample values (David, 1977; Hoeksema et al., 1989). In this study, the statistical correlation between annual precipitation and elevation was around 0.68 to 0.74 (Table 2). Hevesi et al. (1992a) showed a similar statistical correlation between annual precipitation and elevation (0.76), while Phillips et al. (1992) showed a higher statistical correlation (0.82). The ratio of number of sample elevation points to sample precipitation points was similar in this study and the work by Phillips et al. (1992) and so the higher improvement of the estimation precision due to cokriging observed in this latter work was probably caused by the highest spatial correlation between the primary and auxiliary variables. Hevesi et al. (1992a, 1992b) used a higher ratio of number of sample elevation points to number of precipitation points but the space domains of the two variables were different. The estimation precision by using cokriging is improved when the primary variable is greatly undersampled compared to the auxiliary variable but better results are obtained when the interpolation points coincide with sample values of the auxiliary variable (David, 1977; Samper and Carrera, 1990).

CONCLUSIONS

The spatial variability of long-term annual precipitation (APRE), log-transformed APRE (LAPRE), elevation above sea level (ELEV) and log-transformed ELEV (LELEV) has been analyzed and modeled in the region of Aragón (Spain). The spatial correlation between APRE and ELEV, APRE and LELEV, LAPRE and ELEV, and LAPRE and LELEV has also been analyzed and modeled. The respective direct- and cross-semivariogramas have been fitted with gaussian models with nugget effects. Ranges of the direct-semivariogram models for APRE and LAPRE were about 132-136 km, while those of the direct-semivariogram models for ELEV and LELEV were about 156-165 km. Ranges of the cross-semivariograms were the same than those of the respective direct-semivariograms for APRE and LAPRE.

The estimates obtained at 1913 interpolation points by kriging were in average about 11-12 % higher than cokriging estimates when APRE sample values were used, and about 9 % higher when using LAPRE sample values. The positive statistical correlation between annual precipitation and elevation and the higher average elevation of the additional elevation sample points compared to average elevation of the weather stations were the reasons for the higher estimates obtained by cokriging. Nevertheless, for some points of low-elevation cokriging estimates were lower than kriging ones. The four sets of cokriging estimates obtained in this study were in general terms similar and the averages of the percent differences among them was less than 3 %. Nevertheless, the use of ELEV instead of LELEV sample values as the auxiliary variable seemed to overestimate annual precipitation at points of high elevation. Estimates obtained by cokriging reflected more closely the topography of Aragón as shown by the respective isolines maps of the estimates.

For all interpolation points, the use of LAPRE instead of APRE sample values lead to reduced estimation error standard deviations (EESD). The averages of the percent differences among cokriging EESD obtained using LAPRE sample values and cokriging EESD obtained using APRE sample values ranged from -38 to -42 % depending on the use of ELEV or LELEV as the auxiliary variable, respectively. Likewise, for all sample points cokriging EESD were lower than kriging EESD. The averages of the percent differences among cokriging EESD and kriging EESD ranged from -7 to -14 % when APRE sample values were used, while those averages were about -11 % when LAPRE sample values were used.

As final conclusion, the results of this study suggest that an improved estimation of annual precipitation in Aragón was obtained when a multivariate geostatistical approach (cokriging) was used, together a log-transformation of the primary (annual precipitation) and the auxiliary (elevation) variables.

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Table 1. Descriptive statistics of APRE and LAPRE available at the weather stations and ELEV and LELEV available at the weather stations and 1913 additional sample points.

Statistics	APRE (mm)	LAPRE[a]	ELEV[c] (m)	ELEV[d] (m)	LELEV[b,d]
Number	182	182	182	2095	2095
Average	650.2	2764.8	649.6	791.8	2820.6
Minimum	296.0	2470.9	122.0	70.0	1845.1
Maximum	1976.0	3295.8	1660.0	2880.0	3459.4
Median	500.5	2699.3	600.5	720.0	2857.3
Variance	110858.0	39428.1	105327.0	213999.0	73533.1
Coeff. of variation	51.2	7.2	50.0	58.4	9.6
Standard. skewness	7.0	3.2	2.8	18.7	-6.2

[a] Log(mm) x 10^{-3}
[b] Log(m) x 10^{-3}
[c] Elevation at the weather stations
[d] Elevation at the weather stations and 1913 additional sample points

Table 2. Simple linear regression analysis of sample values of APRE and LAPRE on ELEV and LELEV. (n=182).

Dependent variable[a]	Independent variable[b]	Intercept	Slope	Coeff. of correlation
APRE	ELEV	155.6[S]	0.762[S]	0.74[S]
APRE	LELEV	-1885.9[S]	0.922[S]	0.68[S]
LAPRE	ELEV	2472.0[S]	0.451[S]	0.74[S]
LAPRE	LELEV	1169.8[S]	0.580[S]	0.72[S]

[a] APRE, mm; LAPRE, Log(mm) x 10^{-3}
[b] ELEV, m; LELEV, Log(m) x 10^{-3}
[S] Significant at α = 0.05

Table 3. Parameters and cross-validation statistics of the gaussian models fit to the experimental direct-semivariograms for APRE, LAPRE, ELEV and LELEV, and the cross-semivariograms for APRE-ELEV, APRE-LELEV, LAPRE-ELEV and LAPRE-LELEV.

	Model parameters			Cross-valid. statistics		
Semivariog.	Nugget[a]	Sill[a]	Range (km)	PAEE (%)	RMSE (dimensionless)	SMSE
APRE	8260	121050	132	0.413	0.091	0.986
LAPRE	2830	48090	136	0.031	0.091	0.980
ELEV	28950	279890	165	0.514	0.137	0.977
LEELV	6590	109150	156	0.036	0.091	0.970
APRE-ELEV	7330	108150	132	2.097	0.072	1.037
APRE-LELEV	1550	80450	132	3.216	0.088	1.052
LAPRE-ELEV	3850	69700	136	0.256	0.072	0.986
LAPRE-LELEV	1520	53950	136	0.351	0.077	1.030

[a] APRE, mm^2; LAPRE, $[Log(mm)]^2 \times 10^{-6}$; ELEV, m^2; LELEV, $[Log(m)]^2 \times 10^{-6}$; APRE-ELEV, mm m; APRE-LELEV, mm Log(m) x 10^{-3}; LAPRE-ELEV, m Log(mm) x 10^{-3}; LAPRE-LELEV, Log(mm) Log(m) x 10^{-6}

Table 4. Descriptive statistics of the estimates and estimation error standard deviations (EESD) of APRE obtained at 1913 interpolation points for six cases: KP, kriging of APRE; CKPE, cokriging of APRE and ELEV; CKPLE, cokriging of APRE and LELEV; KLP, kriging of LAPRE; CKLPE, cokriging of LAPRE and ELEV; CKLPLE, cokriging of LAPRE and LELEV.

	Estimates of APRE (mm)[a]					
Statistics	KP	CKPE	CKPLE	KLP	CKLPE	CKLPLE
Mean	534.3	601.9	589.9	531.3	593.0	583.6
Minimum	323.0	296.3	209.9	327.3	326.0	279.4
Maximum	1638.7	1866.5	1672.2	1691.5	2520.6	1919.0
Std. deviation	239.6	285.9	254.2	237.1	334.8	282.1
Coef. variation	44.8	47.5	43.1	44.6	56.5	48.3
	EESD of APRE (mm)[a]					
Statistics	KP	CKPE	CKPLE	KLP	CKLPE	CKLPLE
Mean	110.5	93.8	101.0	66.7	58.4	58.3
Minimum	93.8	82.4	91.4	56.6	51.1	52.7
Maximum	324.4	242.6	220.8	198.6	152.9	128.9
Std. deviation	30.4	20.3	16.5	18.6	12.9	9.6
Coef. variation	27.5	21.6	16.3	27.9	22.1	16.5

[a] Coefficient of variation, %

Table 5. Descriptive statistics of the percent differences, for each of 1913 interpolation points, among the estimates of APRE obtained for six cases: KP, kriging of APRE; CKPE, cokriging of APRE and ELEV; CKPLE, cokriging of APRE and LELEV; KLP, kriging of LAPRE; CKLPE, cokriging of LAPRE and ELEV; CKLPLE, cokriging of LAPRE and LELEV.

Cases	Mean (%)	Minimum (%)	Maximum (%)
CKPE vs KP	12.8	-21.7	122.0
CKPLE vs KP	11.3	-40.5	69.8
KLP vs KP	-0.4	-5.0	6.4
CKLPE vs KP	9.0	-16.5	87.5
CKLPLE vs KP	8.7	-26.6	49.3
CKPLE vs CKPE	-0.8	19.6	-33.7
KLP vs CKPE	-9.8	22.3	-53.8
CKLPE vs CKPE	-2.8	-22.7	37.4
CKLPLE vs CKPE	-2.7	16.3	-33.5
KLP vs CKPLE	-8.9	-39.6	66.2
CKLPE vs CKPLE	-1.4	-23.3	67.1
CKLPLE vs CKPLE	-1.7	-14.4	33.1
CKLPE vs KLP	9.4	-12.8	89.6
CKLPLE vs KLP	9.2	-25.7	45.8
CKLPLE vs CKLPE	0.3	16.6	-29.2

Table 6. Descriptive statistics of the percent differences, for each of 1913 interpolation points, among the estimation error standard deviations (EESD) of APRE obtained for six cases: KP, kriging of APRE; CKPE, cokriging of APRE and ELEV; CKPLE, cokriging of APRE and LELEV; KLP, kriging of LAPRE; CKLPE, cokriging of LAPRE and ELEV; CKLPLE, cokriging of LAPRE and LELEV.

Cases	Mean (%)	Minimum (%)	Maximum (%)
CKPE vs KP	-14.30	-12.09	-27.61
CKPLE vs KP	-6.99	-2.47	-32.93
CKLPE vs KLP	-11.62	-9.59	-24.60
CKLPLE vs KLP	-11.00	-6.65	-35.81
CKLPE vs CKPE	-37.79	-36.66	-37.97
CKLPLE vs CKPLE	-42.28	-41.65	-42.52
CKLPLE vs CKLPE	0.59	3.26	-15.71

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Figure 8. Percent differences among cokriging (case CKLPLE) and kriging (case KLP) estimation error standard deviations (EESD) versus the latitude (UTM North-south). (n=1913).

Figure 1. Map showing the location of Aragón.

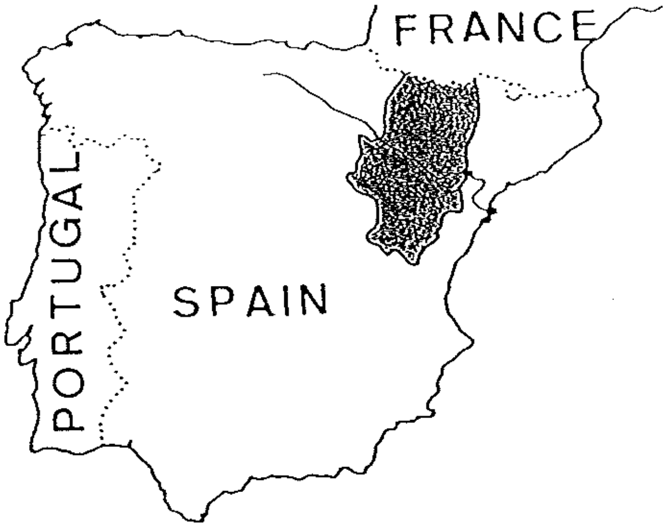
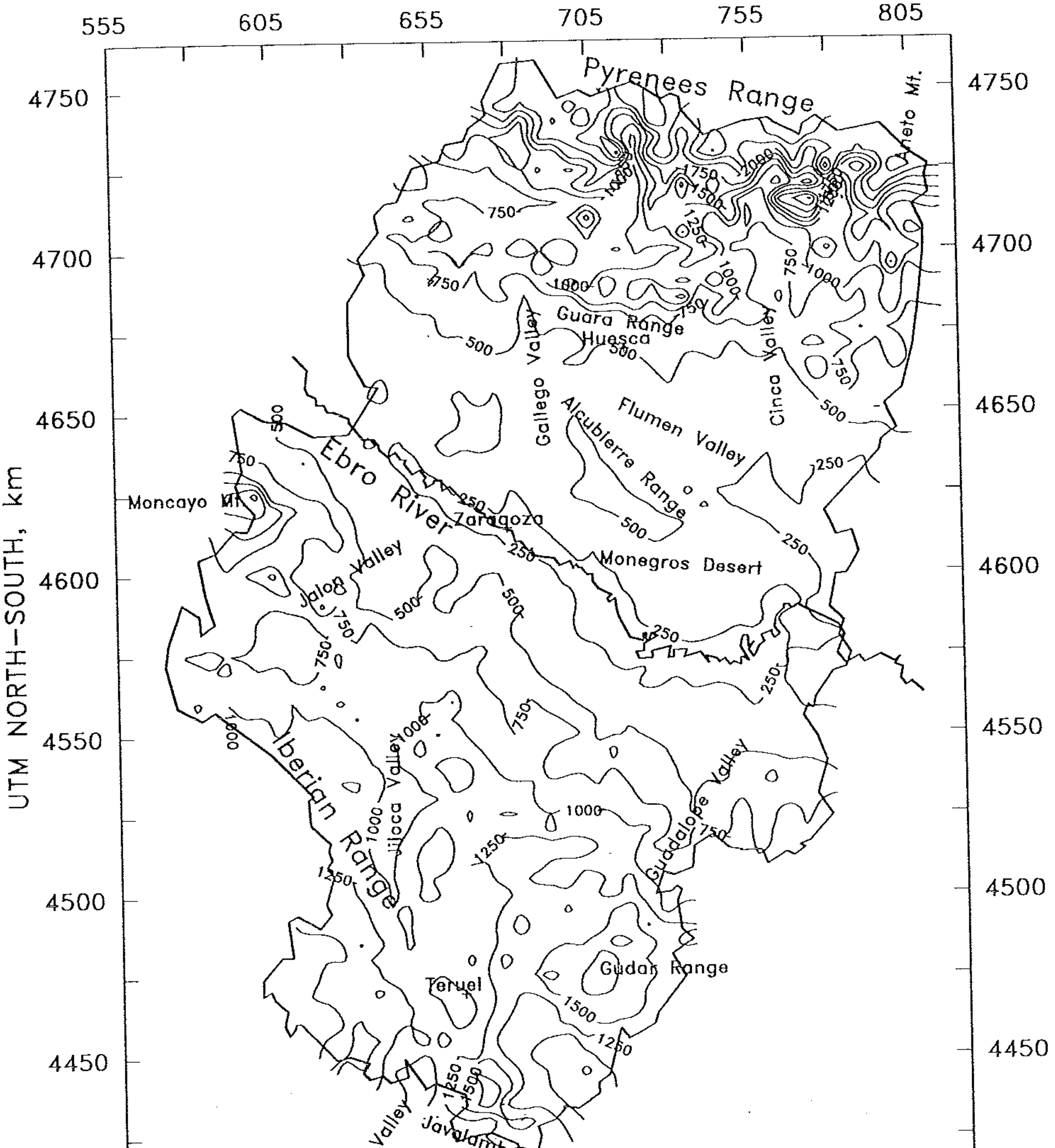

FRANCE
PORTUGAL
SPAIN

Figure 2. Isolines of elevation above sea level (m) of Aragón.


Pyrenees Range
Aneto Mt.
Guara Range
Huesca
Gallego Valley
Alcubierre Range
Flumen Valley
Cinca Valley
Ebro River
Zaragoza
Monegros Desert
Moncayo Mt.
Jalon Valley
Iberian Range
Jiloca Valley
Guadalope Valley
Gudar Range
Teruel
Turia Valley
Javalambre Range
UTM NORTH-SOUTH, km
UTM EAST-WEST, km
555
605
655
705
755
805
4400
4450
4500
4550
4600
4650
4700
4750

		Primary variable		
		APRE	LAPRE	
	None	KP	KLP	KRIGING
Auxiliary variable	ELEV	CKPE	CKLPE	COKRIGING
	LELEV	CKPLE	CKLPLE	

Figure 3. Scheme of the six cases compared in this study, resulting of the application of two geostatistical interpolation methods, kriging and cokriging, to two variables, annual precipitation (APRE) and elevation (ELEV), and their respective log-transformations (LAPRE and LELEV).

Figure 4. Percent differences among cokriging (case CKLPLE) and kriging (case KLP) estimates of APRE versus elevation. (n=1913).

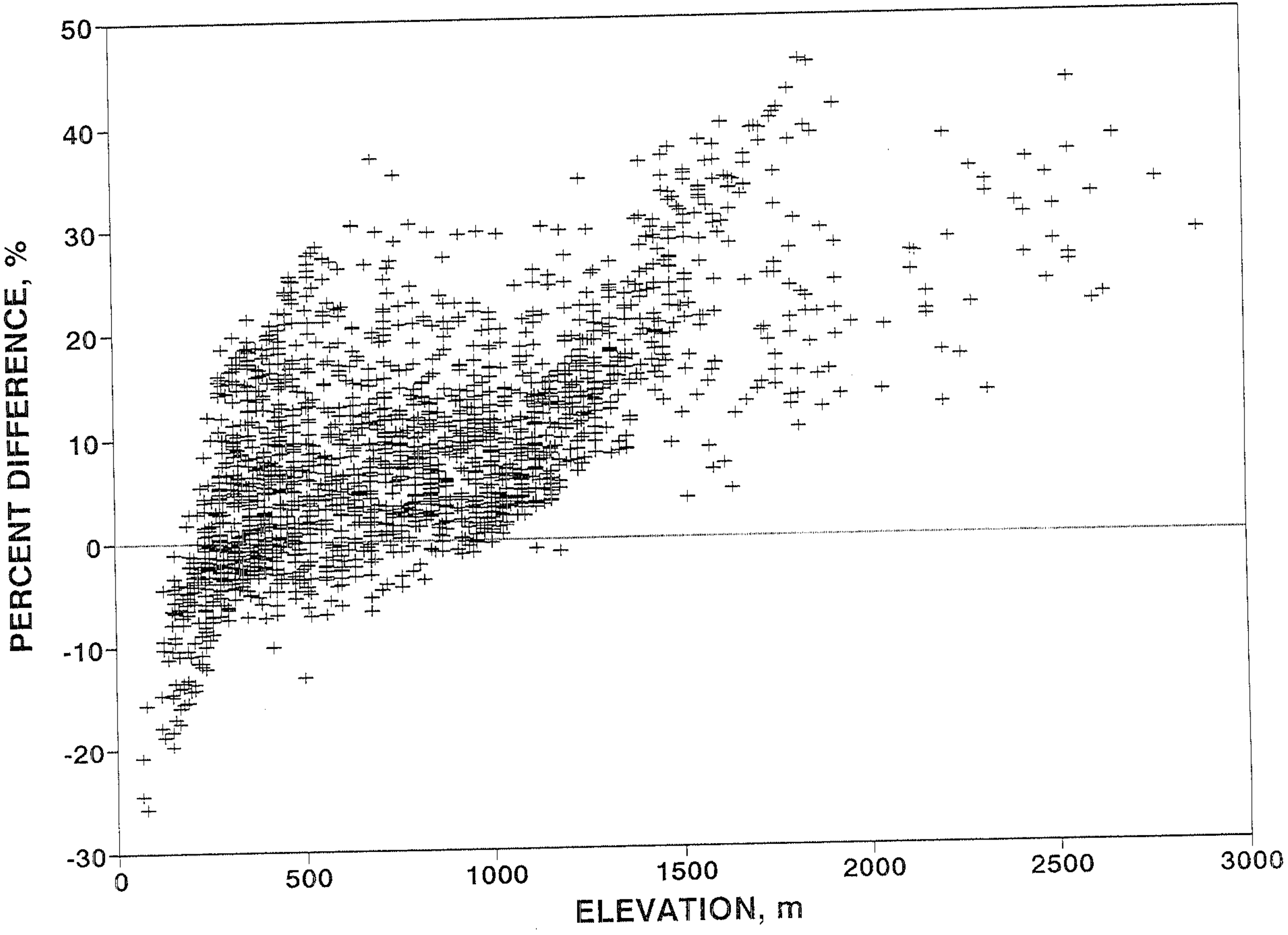
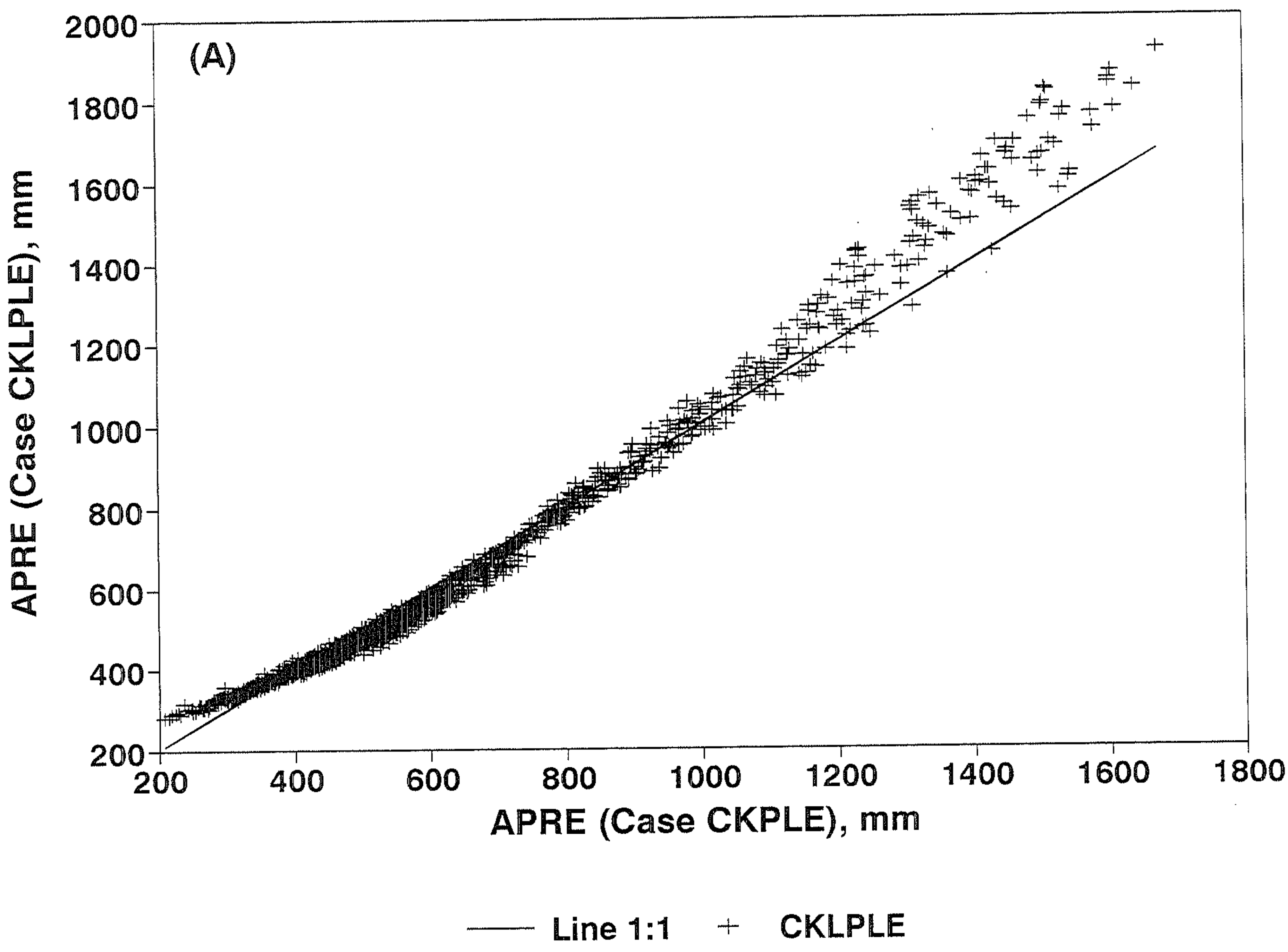

PERCENT DIFFERENCE, %
50
40
30
20
10
0
-10
-20
-30
0
500
1000
1500
2000
2500
3000
ELEVATION, m

Figure 5. Cokriging estimates of APRE obtained with sample values of (A) LAPRE and LELEV (case CKLPLE) vs APRE and LELEV (case CKPLE); and (B) LAPRE and ELEV (case CKLPE) vs those obtained with cokriging of LAPRE and LELEV (case CKLPLE). (n=1913).


(A)
APRE (Case CKLPLE), mm
2000
1800
1600
1400
1200
1000
800
600
400
200
200
400
600
800
1000
1200
1400
1600
1800
APRE (Case CKPLE), mm
Line 1:1
CKLPLE

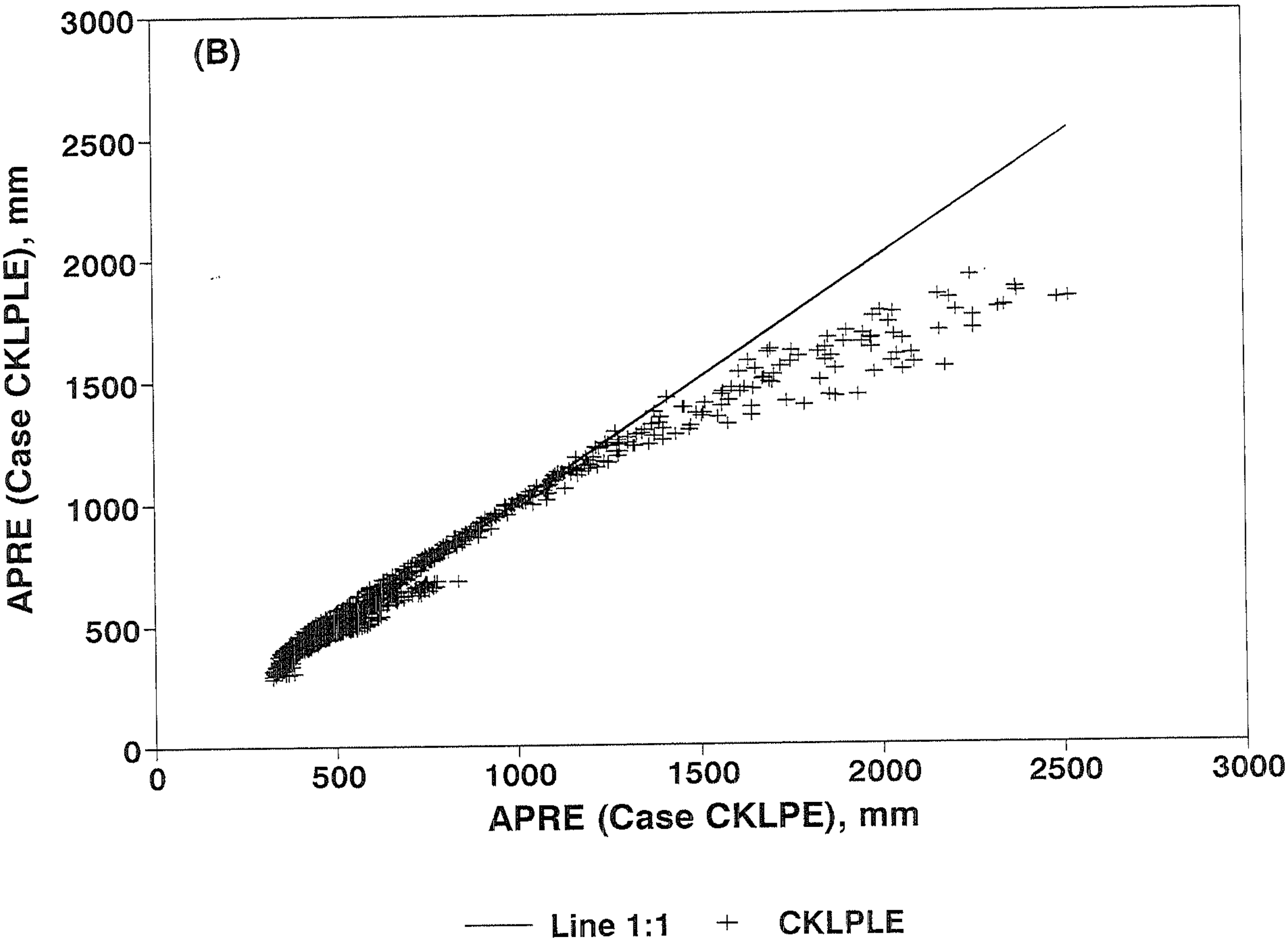
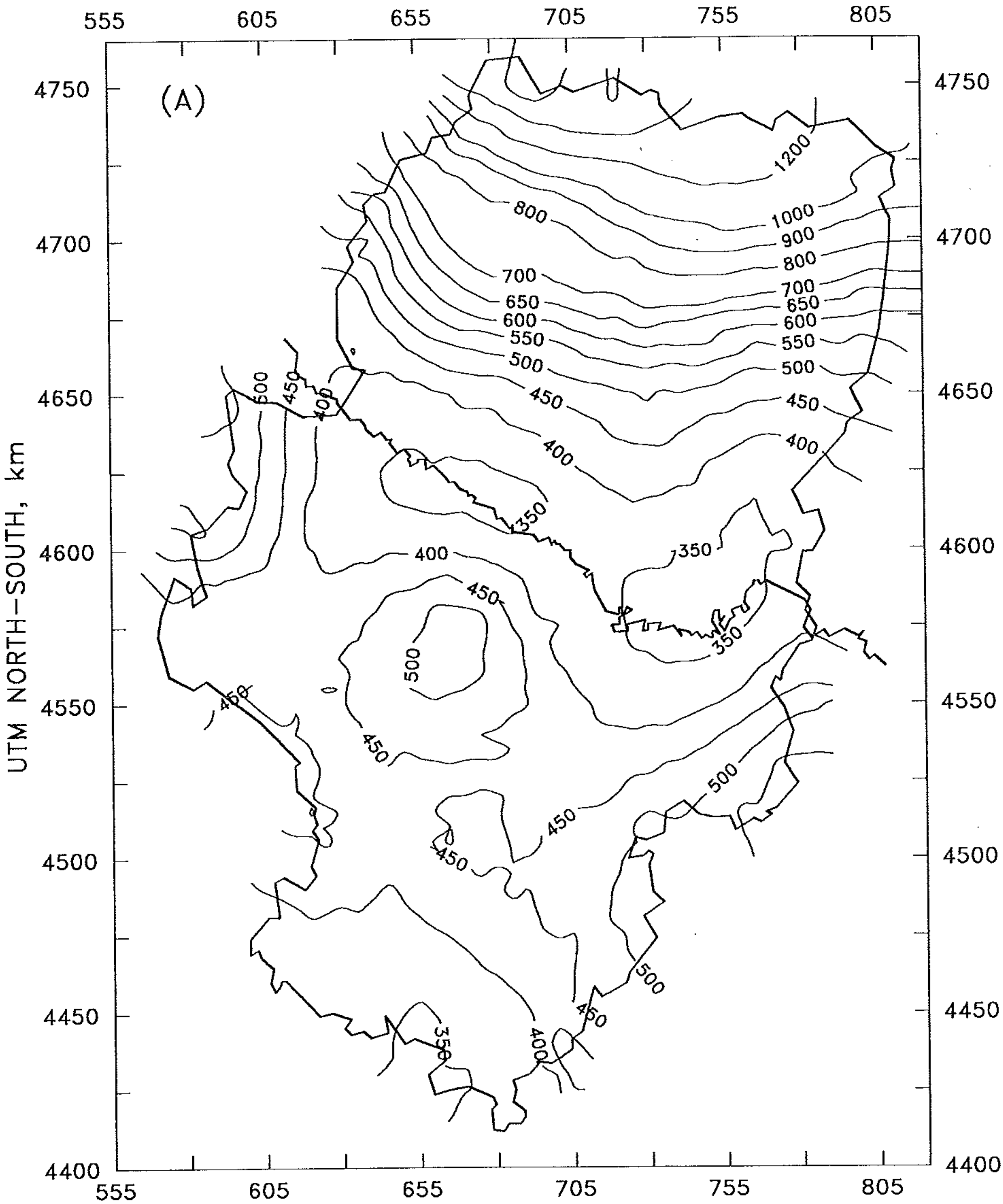

(B)
APRE (Case CKLPLE), mm
APRE (Case CKLPE), mm
0
500
1000
1500
2000
2500
3000
Line 1:1
CKLPLE

Figure 6. Maps of isolines of APRE. (A) Kriging (case KLP). (B). Cokriging (case CKLPLE).



(A)
555
605
655
705
755
805
4750
4700
4650
4600
4550
4500
4450
4400
UTM NORTH-SOUTH, km
UTM EAST-WEST, km
1200
1000
900
800
700
650
600
550
500
450
400
350

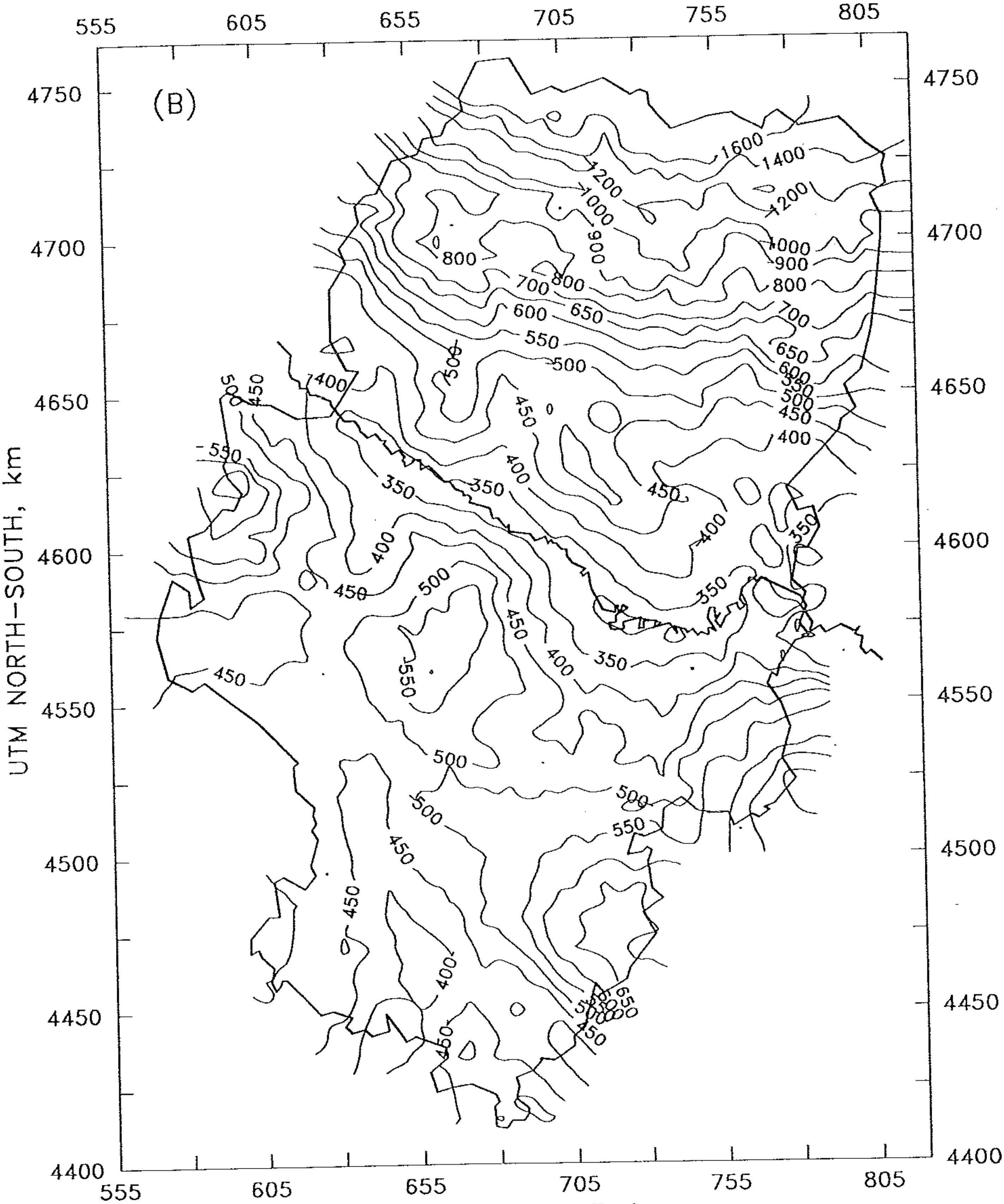
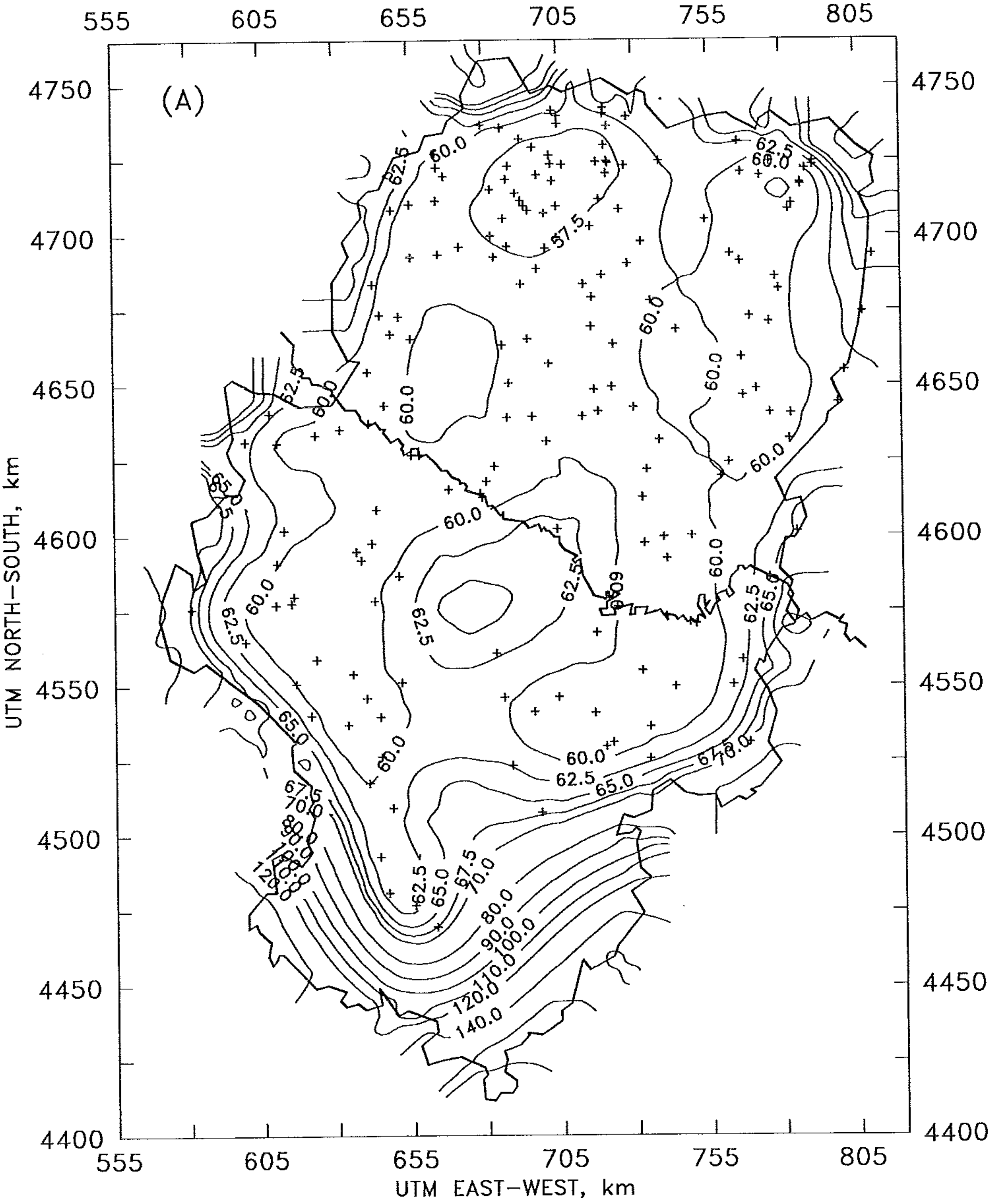
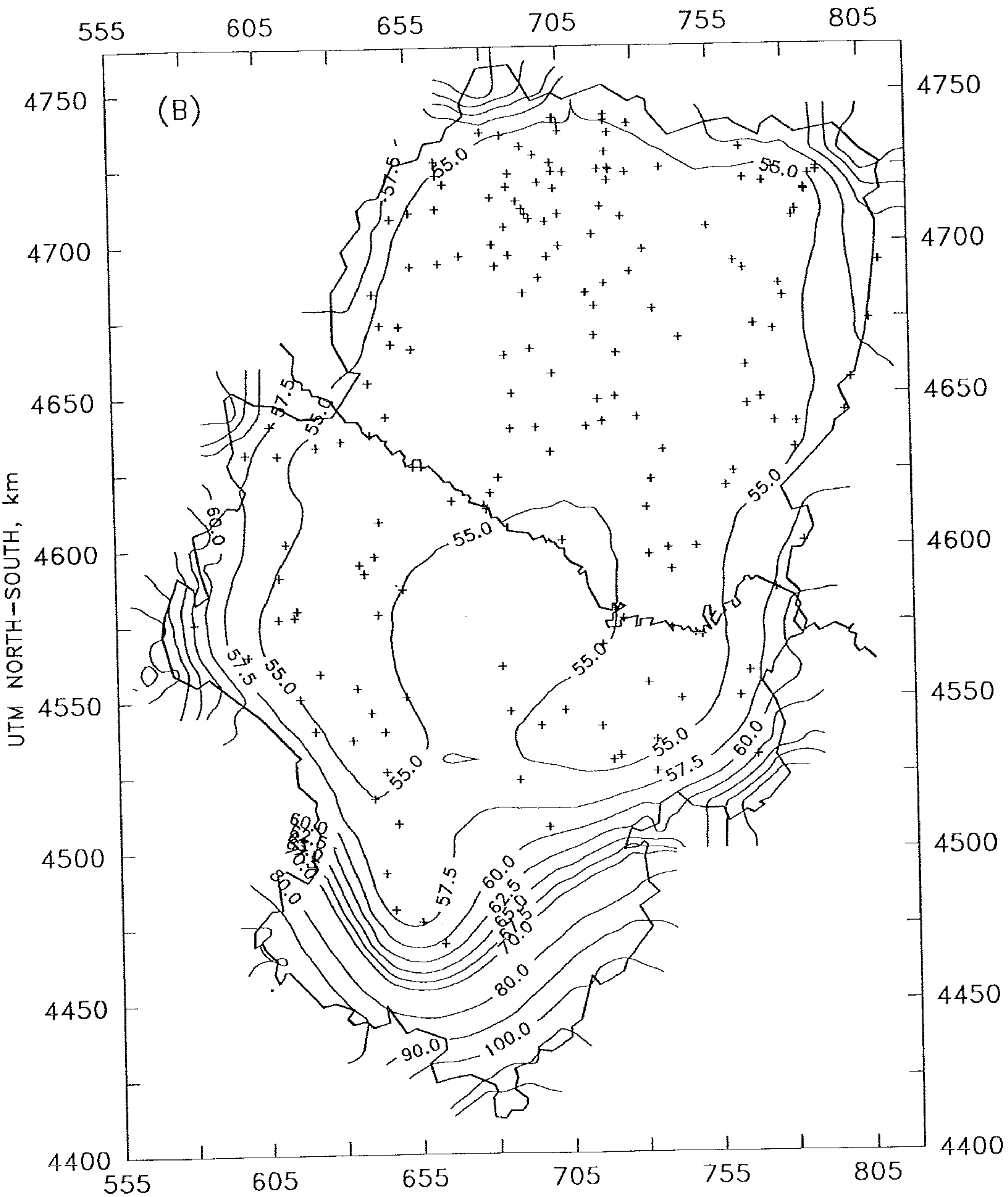

(B)
UTM NORTH-SOUTH, km
UTM EAST-WEST, km
555
605
655
705
755
805
4400
4450
4500
4550
4600
4650
4700
4750

Figure 7. Maps of isolines of estimation error standard deviations (EESD) of APRE. (A) Kriging (case KLP). (B) Cokriging (case CKLPLE). +, available weather stations.

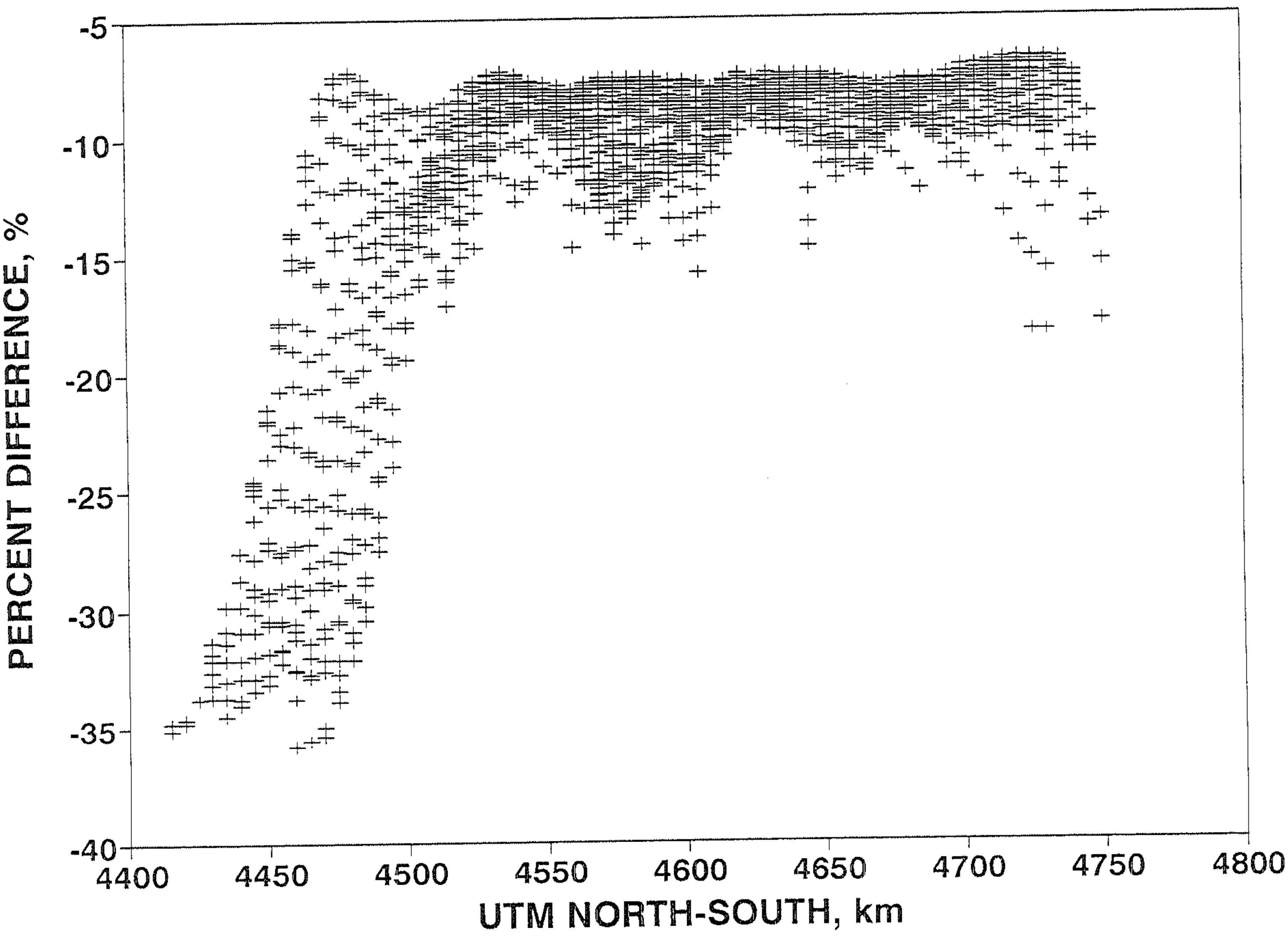


(A)
UTM NORTH-SOUTH, km
UTM EAST-WEST, km
555
605
655
705
755
805
4400
4450
4500
4550
4600
4650
4700
4750
60.0
62.5
65.0
67.5
70.0
80.0
90.0
100.0
110.0
120.0
140.0



(B)
555
605
655
705
755
805
4750
4700
4650
4600
4550
4500
4450
4400
UTM NORTH-SOUTH, km
UTM EAST-WEST, km
55.0
57.5
60.0
62.5
65.0
67.5
70.0
80.0
90.0
100.0

Figure 8. Percent differences among cokriging (case CKLPLE) and kriging (case KLP) estimation error standard deviations (EESD) versus the latitude (UTM North-south). (n=1913).



PERCENT DIFFERENCE, %
-5
-10
-15
-20
-25
-30
-35
-40
4400
4450
4500
4550
4600
4650
4700
4750
4800
UTM NORTH-SOUTH, km