

## AN ABSTRACT OF THE THESIS OF

Jeffery L. Nuss for the degree of Master of Science in Civil Engineering presented on September 21, 1989.

Title: Analysis of Evapotranspiration for Various Climatic Regimes Using Geostatistics

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Dr. Richard H. Cuenca

Research was conducted to determine the applicability of using the theory of regionalized variables or geostatistics in characterizing the spatial variability of reference evapotranspiration (ET<sub>r</sub>) over various climatic regimes for the state of Oregon. The state was divided into five climatic regions based on topographic features and local meteorological conditions: 1) Coast, 2) Willamette Valley, 3) Southwestern Valley, 4) North East, and 5) South East. The local ET<sub>r</sub> estimates provided from the FAO-modified Blaney Criddle method were divided into their respective regions and averaged over the three years.

The variogram analysis was performed on the average ET<sub>r</sub> estimates for May through September in each region. Model variograms were fitted to the calculated sample variograms and a cross validation routine performed to test the chosen model. For four out of the five subregions, a verified spherical model was obtained for the individual months. Difficulties related to the low number of samples representing the region made it difficult to confirm model variograms in region 3.

The model variograms determined for the average ET<sub>r</sub> estimates were used as the model variograms for the individual years (1985, 1986, 1987) to test the hypothesis that one model variogram could represent the spatial correlation of ET<sub>r</sub> for the region. Due to the inconsistencies seen in the analysis, no valid conclusions could be made to support this hypothesis. It is recommended that developing the model variograms from long term average ET<sub>r</sub> estimates instead of the short three year average could provide better results when applied to individual years.

Kriging was performed on the average ETr estimates for July and September in regions 1, 2, 4, and 5. From the kriging analysis, estimates of ETr along with the standard deviation over a grid representing the region were produced. Contour maps were plotted using the gridded information of kriged ETr and standard deviation of the kriged estimates. The results of these contour maps proved to be a good representation of the ETr estimates within most of the regions. It was noticed that the values of ETr of individual meteorological stations within the regions influenced the shape of the contour lines and the shape did not necessarily correspond to topographic effects in Oregon. One explanation is that the weather stations used for the ETr estimates are generally representative of the valleys in each region. For use in hydrologic modeling or irrigation system design and scheduling in valleys, the kriged ETr estimates could be very satisfactory. However, for use in large scale hydrologic modeling or global circulation models, a method to account for the topographic effects must be included in the kriged ETr estimates. A method that might prove successful is developing a spatial correlation between ETr and elevation through a geostatistical technique termed cokriging.

Another problem with the regional analysis was comparison at regional boundaries. To effectively utilize these contour maps for the whole state, there must be some method to deal with the transition zones between regions. A possibility is to combine kriged estimates from each region into one file representing the whole state and producing contour plots for the overall data file.

The use of geostatistics is becoming more common in hydrology and its use is expected to grow. From this work, geostatistics proved to be a possible tool to generate estimates and computerized plots of reference evapotranspiration (ETr). However, there are difficulties to overcome for geostatistics to be applied operationally in estimating regional evapotranspiration.

**Analysis of Evapotranspiration  
for Various Climatic Regimes Using  
Geostatistics**

by  
Jeffery L. Nuss

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APPROVED:

*Redacted for Privacy*

Professor of Civil Engineering

*Redacted for Privacy*

Head of Department of Civil Engineering

*Redacted for Privacy*

Dean of Graduate

Thesis presented by

Jeffery L. Nuss

Date thesis is presented

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# **Analysis of Evapotranspiration for Various Climatic Regimes Using Geostatistics**

## **1 INTRODUCTION**

### **1.1 STATEMENT OF THE PROBLEM**

The rate of evapotranspiration from the earth's surface is an important component in the hydrologic balance of the earth and has been of considerable interest and concern to scientists and engineers in the agricultural community since the 1950's. Accurate information on evapotranspiration rates is essential in irrigation management, hydrologic studies, crop management practices, and global climate models. In irrigated areas of the world, an increasing demand for water has stressed the importance in understanding the losses and use of water at scales ranging from local to regional.

With this increasing demand on the water supply, the agricultural community must take measures to insure an optimal use of this limited supply. Currently, designing an irrigation system and scheduling the amount and frequency of the water applied to a crop for a given region uses a locally estimated reference evapotranspiration rate from a weather station representative of the site. Reference evapotranspiration is a term used for evapotranspiration of a specific crop, usually grass, under a set of standard conditions. Doorenbos and Pruitt (1977) defined reference evapotranspiration (ET<sub>r</sub>) as "the rate of evapotranspiration from an extensive surface of 8 to 15 centimeters tall green grass cover of uniform height, actively growing, completely shading the ground, and not short of water." Local estimating scales for evapotranspiration are normally considered to be a radius of 10 km from the point of reference (Amegee, 1985). The region for which the irrigation system is designed or for which irrigation is scheduled may be considerably larger than what the weather station represents. This extrapolation of ET<sub>r</sub> from local estimating scales to a regional scale introduces errors which

may cause crops to be overirrigated or underirrigated and an overdesign or underdesign of water storage reservoirs, wastewater treatment plants, and other systems relying on knowledge of regional evapotranspiration. Achieving an optimal use of the water supply for a given region requires an effort to improve the accuracy of regional ETr estimates and to quantify the error associated with the application of local ETr estimates to a region.

Another concern which has accelerated interest in the analysis of evapotranspiration on a regional scale is the attention to global climatic change. Regionalized evapotranspiration estimates are inputs to global circulation models (GCMs) used to predict both short-term and long-term climatic changes. These models normally operate on a minimum grid size ranging from 100 to 500 km (Cuenca and Amegee, 1987).

The combination of the increasing demand for knowledge which would improve the use and management of this limited water supply and recent concerns over global climatic change have encouraged and justified attempts to develop methods for analyzing or quantifying evapotranspiration on a regional scale. Developments in the field of remote sensing have suggested the potential for deriving regionalized estimates of evapotranspiration using the crop canopy temperature. This temperature is sensed by a satellite or other remote sensing instruments like the NASA C-130 aircraft, and is coupled with ground based measurements to model the evaporative flux from the earth's surface. Much of the technology in collecting the data exists and is well understood. However, the coupling of remote sensing data with ground based measurements to obtain accurate measurements of evaporative flux requires more research. Although the resulting formulas offer promising results, their validity has not been adequately verified with respect to soil moisture and cloudy sky conditions to allow operational estimates of regional ETr (Schmugge, 1978; Bernard et al., 1981).

A straight forward procedure (Baier, 1979) for estimating regional evapotranspiration consists of using local estimates over a small homogeneous area and applying a weighting factor according to the relative surface area. This particular method requires a large number of

weather stations collecting data to achieve an accurate estimate of regional evapotranspiration. A desired method is to develop a model for ETr based on its spatial variability. Such a model would determine regional estimates of ETr based on the variation of ETr as a function of distance between available data points. This model would provide a more accurate estimate of ETr at locations where no climatic data are available compared to a method which does not take into consideration the structure of ETr variability (Amegee, 1985). The improved accuracy of estimated regional evapotranspiration would improve accuracy of irrigation systems, global circulation models, and be applicable to regional water resources development and management.

## **1.2 PREVIOUS WORK**

In 1985, Kodjo Y. Amegee completed a Doctor of Philosophy in Civil Engineering with his thesis topic being application of geostatistics to regional evapotranspiration. Amegee studied how well the theory of regionalized variables could be applied to evapotranspiration. The findings of this research indicated that the spatial variability of reference evapotranspiration over large geographical areas could be described by model variograms and this information could be used to predict evapotranspiration rates by means of kriging (Amegee, 1985). Recommendations from this research suggested removing the bias associated with a model representative of the whole state of Oregon by deriving individual model variograms for climatic regions within the state.

## **1.3 OBJECTIVES AND SCOPE**

This thesis presents an attempt to model regional evapotranspiration for various climatic regimes based on its spatial variability within each regime. The general objective was to compare the statewide regional ETr estimates computed by Amegee (1985) with an analysis of

regional ETr estimates of five climatic regions using geostatistics. The project was a direct continuation of the research of Amegge (1985) into the application of geostatistics in estimating regional evapotranspiration. The specific objectives of this work were the following:

1. The first objective was to determine if an acceptable model variogram could be produced for the different climatic regions. A model variogram, defined in the next chapter, was fitted to the data of estimated ETr at different locations to relate the change in estimated ETr to the distance between stations. The data used to test this objective were derived by calculating the average monthly ETr for May through September from the three years (1985, 1986, and 1987) of available data. The reason for using an average ETr from the three years is explained in the second objective.

2. The second objective was to observe if the model variogram developed for the average ETr could be used as the model variogram for the individual years. The purpose was to determine if a model variogram could be fitted to long term average ETr data then be used as the model variogram for ETr estimates gathered year to year, month to month, or week to week.

3. Assuming an acceptable model variogram could be produced for the individual months in each region, the last objective was to apply kriging to estimate reference evapotranspiration (ETr) over a grid of locations throughout the region and to produce contour maps of the regional ETr.

The scope of this project was limited to the state of Oregon. Estimations of reference evapotranspiration rates were made at 180 locations for 1985, 1986, and 1987 during the months of May through September. Within the state of Oregon, five climatic regions were identified. For each region, model variograms were developed for each month and year. These model variograms were used to krige reference evapotranspiration for a grid of locations throughout the regions. Contour maps of estimated ETr for each region were plotted.

## **2 LITERATURE REVIEW**

This chapter is broken down into three main topics: description of evapotranspiration, local and regional evapotranspiration (ET) estimating methods, and fundamentals of geostatistics. The first topic gives basic definitions followed by a brief review of the methods used for the estimation of ET both on a local and regional scale. The last topic is a review of concepts in the theory of regionalized variables or geostatistics.

### **2.1 BASIC DEFINITIONS**

Consistent definitions for evapotranspiration estimates are extremely important in maintaining communication within the research community. The following definitions are based on those found in the American Society of Civil Engineers (ASCE) report, "Consumptive Use of Water and Irrigation Water Requirements" (Jensen, 1974).

#### **Evapotranspiration**

Evapotranspiration is the loss of water from the ground to the atmosphere through water vaporization. The two main components making up evapotranspiration are water evaporated from the soil surface and water lost through plant surfaces which is termed transpiration. Figure 1 provides a schematic of the hydrologic balance in which a large role is played by evapotranspiration. As a global average, 57% of the annual precipitation falling over the land is returned to the atmosphere by evapotranspiration (Budyko et al., 1982). Evapotranspiration amounts to about 70% of the annual precipitation of the United States, and more than 90% in the arid areas of the Western United States, while it could be up to 100% in some desert areas (Hamon, 1966).

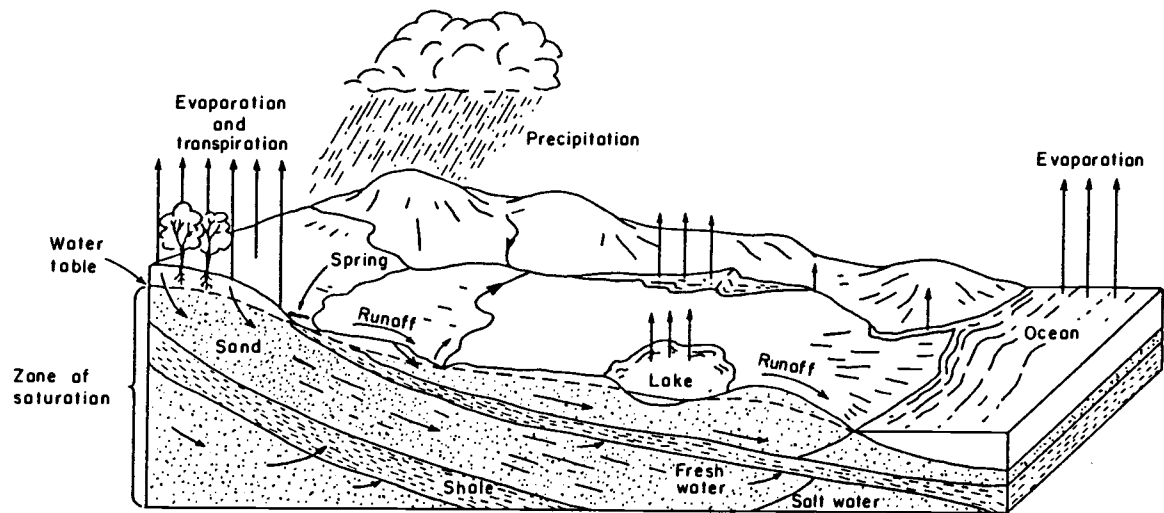


Figure 1: Schematic of the Hydrologic Balance (taken from Cuenca, 1989)

### Potential Evapotranspiration

Potential evapotranspiration is the maximum rate at which water can be evaporated from the soil surface and transpired by a plant. Many researchers comment on the vagueness of this term. Due to this vagueness, a move to the term reference evapotranspiration has been occurring in many subject areas.

### Reference Evapotranspiration

Two definitions are commonly used in defining reference evapotranspiration (ET<sub>r</sub>). Doorenbos and Pruitt (1977) defined it as "the rate of evapotranspiration from an extensive surface of 8 to 15 centimeters green grass cover of uniform height, actively growing,

completely shading the ground, and not short of water". The second definition of ETr is from Jensen et al. (1971) and is defined as "the upper limit or maximum evapotranspiration that occurs under given climatic conditions with a field having a well watered agricultural crop with an aerodynamically rough surface, such as alfalfa, with 30 to 50 centimeters of top growth". Reference evapotranspiration in this work uses grass as the reference crop which corresponds to the definition provided by Doorenbos and Pruitt (1977).

## **2.2 REGIONAL VS LOCAL EVAPOTRANSPIRATION ESTIMATING METHODS**

### **2.2.1 LOCAL EVAPOTRANSPIRATION ESTIMATING METHODS**

An accurate account of methods for estimating ET from climatic data is not available, but the total must be in the dozens (Burman et al., 1983). The Penman equation (Penman, 1948) was introduced 41 years ago and is based on the combination approach of net radiation and a wind function. Much of the Penman equation is based on theory, however some form of empiricism exists to account for simplifications needed for practical use. Other more practical empirical methods exist and are widely used in water resource management and engineering projects.

Seventeen empirical methods were identified, examined, and compared by Erpenbeck (1981) at fourteen meteorological sites in the state of Washington. Seven of these methods used air temperature as the only weather parameter in estimating ETr. Air temperature is termed a primary weather parameter because of its common availability. Primary parameter refers to a parameter for which data are available for each day or month in each year. Ten of these methods used a combination of air temperature as the primary weather input plus secondary weather data on solar radiation, windspeed, and saturation deficit of the air. Secondary weather data are long-term averages of monthly data. The secondary weather data provide a means to adjust estimated ETr based on the general climatic conditions. Doorenbos



and Pruitt (1977) concluded that one can improve ETr by applying local calibration or at least an adjustment that considers the general climatic conditions. These secondary data are typically available in a limited number of stations in a region.

Erpenbeck (1981) chose the Food and Agriculture Organization (FAO)- modified Blaney Criddle method (Doorenbos and Pruitt, 1977) as the best state-wide ET estimating method. The selection was based on the weather data available throughout the state of Washington and a statistical ranking using the coefficient of determination for each estimating method compared to lysimeter measurements. Another comparison among ETr estimating methods was performed by Allen and Brockway (1982). They selected the FAO-modified Blaney Criddle method as the best state-wide ET method based on accuracy and the primary data requirement of only air temperature. Allen and Brockway (1982) compared the Soil Conservation Service (SCS)-modified Blaney Criddle, the FAO-modified methods (i.e. FAO radiation, FAO-modified Blaney Criddle, FAO Penman, and FAO corrected Penman), the Jensen-Haise, standard Penman, and Wright modified Penman. The methods were evaluated using daily weather data from the USDA-ARS research center at Kimberly, Idaho (Twin Falls, WSO).

For the state of Oregon, Basketfield (1984) examined and compared two temperature-based ET estimating methods: the SCS modified Blaney Criddle (SCS-BC) and the FAO-modified Blaney Criddle (FAO-modified BC). Results indicated that the SCS-BC method seriously underpredicted crop ET at relatively high-altitude and semiarid locations (Basketfield, 1984). Basketfield selected the FAO-modified BC with adjustments developed by USDA to produce reference evapotranspiration, crop evapotranspiration, and irrigation requirements for selected Oregon locations. Comparison between Basketfield's estimates for ET and net irrigation requirements (NIRR) and those produced by Watt et al. (1968) for the state of Oregon led to recommendation of a revision of irrigation requirements for Oregon. The FAO-modified BC method with USDA adjustments was chosen for both the work performed in the revision and this thesis because the studies performed in Washington (James et al., 1982), Idaho (Allen

and Brockway, 1983), and Oregon (Basketfield, 1984) indicated that this method would be more accurate than any other temperature-based method and make good use of temperature data available at many sites in Oregon. The following is a review of the FAO-modified Blaney Criddle method.

### 2.2.1.1 FAO Modified Blaney Criddle Method

FAO provided funds to publish guidelines for predicting crop water requirements. The work was conducted by Doorenbos and Pruitt using data from 13 sites representing various climates around the world. The data used were meteorological and lysimeter data provided by the United Nations. The work produced a modification to the original Blaney Criddle Method by estimating  $ET_r$  using temperature as a primary weather parameter and adjusting for additional effects of local meteorological conditions by using general estimates or ranges of relative humidity, sunshine hours, and wind speed. Use of humidity, sunshine hours, and wind speed provided an improved prediction of the effect of climate on evapotranspiration (Doorenbos and Pruitt, 1977). The following equation is the result of the analysis of Doorenbos and Pruitt, (1977):

$$ET_r = \{a + b[p(0.46T + 8.13)]\} \left(1 + \frac{Elev}{10000}\right) \quad (1)$$

where

$ET_r$  = reference crop ET for grass, mm/d

$p$  = percent of annual sunshine during month on a daily basis

$T$  = mean temperature, °C

$a, b$  = climatic calibration coefficients

$Elev$  = station elevation, m

The term in the brackets  $[\bar{p}(0.467 + 8.13)]$  is identical to the original Blaney Criddle method. The contribution of Doorenbos and Pruitt was in the  $a$  and  $b$  coefficients which help account for the local climatic conditions. The  $a$  and  $b$  climatic calibration coefficients were produced by a step-wise regression analysis on meteorological and lysimeter data from the FAO project. The FAO report gave the following equation for the  $a$  coefficient and a computerized look-up table for the  $b$  coefficient (refer to Table 1):

$$a = 0.0043(RH_{\min}) - \left(\frac{n}{N}\right) - 1.41 \quad (2)$$

where

$RH_{\min}$  = minimum relative humidity, percent

$n/N$  = ratio of actual to maximum sunshine hours, fraction

Frevert et al. (1983) published a regression equation for  $b$  based on the original computerized look-up table produced by Doorenbos and Pruitt (1977). Further simplification of the equation of Frevert et al. (1983) was performed by Cuenca and Jensen (1988) resulting in the following  $b$  coefficient:

$$b = 0.82 - 0.0041(RH_{\min}) + 1.07\left(\frac{n}{N}\right) + 0.066(U_{\text{day}}) - 0.006(RH_{\min})\left(\frac{n}{N}\right) - 0.0006(RH_{\min})(U_{\text{day}}) \quad (3)$$

where

$U_{\text{day}}$  = daytime windspeed at 2 m height, m/s

TABLE 1: Values of  $b$  as function of RHmin, Uday, and  $n/N$ 

n/N	RHmin (%)						Uday (m/sec)
	0	20	40	60	80	100	
0.0	0.84	0.80	0.74	0.64	0.52	0.38	0
0.2	1.03	0.95	0.87	0.76	0.63	0.48	
0.4	1.22	1.10	1.01	0.88	0.74	0.57	
0.6	1.38	1.24	1.13	0.99	0.85	0.66	
0.8	1.54	1.37	1.25	1.09	0.94	0.75	
1.0	1.68	1.50	1.36	1.18	1.04	0.84	
0.0	0.79	0.90	0.81	0.68	0.54	0.40	2
0.2	1.19	1.08	0.96	0.84	0.66	0.50	
0.4	1.41	1.26	1.11	0.97	0.77	0.60	
0.6	1.60	1.42	1.25	1.09	0.89	0.70	
0.8	1.79	1.59	1.39	1.21	1.01	0.79	
1.0	1.98	1.74	1.52	1.31	1.11	0.89	
0.0	1.08	0.98	0.87	0.72	0.56	0.42	4
0.2	1.33	1.18	1.03	0.87	0.69	0.52	
0.4	1.56	1.38	1.19	1.02	0.82	0.62	
0.6	1.78	1.56	1.34	1.15	0.94	0.73	
0.8	2.00	1.74	1.50	1.28	1.05	0.83	
1.0	2.19	1.90	1.64	1.39	1.16	0.92	
0.0	1.18	1.06	0.92	0.74	0.58	0.43	6
0.2	1.44	1.27	1.10	0.91	0.72	0.54	
0.4	1.70	1.48	1.27	1.06	0.85	0.64	
0.6	1.94	1.67	1.44	1.21	0.97	0.75	
0.8	2.18	1.86	1.59	1.34	1.09	0.85	
1.0	2.39	2.03	1.74	1.46	1.20	0.95	
0.0	1.26	1.11	0.96	0.76	0.60	0.44	8
0.2	1.52	1.34	1.14	0.93	0.74	0.55	
0.4	1.79	1.56	1.32	1.10	0.87	0.66	
0.6	2.05	1.76	1.49	1.25	1.00	0.77	
0.8	2.30	1.96	1.66	1.39	1.12	0.87	
1.0	2.54	2.14	1.82	1.52	1.24	0.98	
0.0	1.29	1.15	0.98	0.78	0.61	0.45	10
0.2	1.58	1.38	1.17	0.96	0.75	0.56	
0.4	1.86	1.61	1.36	1.13	0.89	0.68	
0.6	2.13	1.83	1.54	1.28	1.03	0.79	
0.8	2.39	2.03	1.71	1.43	1.15	0.89	
1.0	2.63	2.22	1.86	1.56	1.27	1.00	

Units for  $RH_{min}$  and  $n/N$  are indicated in Eq. (2). If the daytime wind speed is measured at a height other than 2 meters, application of the log-wind law is used to adjust the measured height to 2 meters. The log-wing law is given in the following equation:

$$U_{2m} = U_z \left( \frac{2.0}{z} \right)^{0.2} \quad (4)$$

where

$U_{2m}$  = equivalent wind speed at 2 m

$U_z$  = wind speed measured at height  $z$

$z$  = height of measurement, m

#### 2.2.1.2 Additional Adjustments to FAO-Modified BC

Additional adjustments to the FAO-modified Blaney Criddle were derived by Allen and Brockway (1982) at the United States Department of Agriculture (USDA) lysimeter site located at the Snake River Water Conservation Laboratory in Kimberly, Idaho. The lysimeter at Kimberly is maintained in alfalfa. Only the most important aspects of the adjustments are discussed. Complete details of the work are found in the publication by Allen and Brockway (1982).

Two reasons existed for the additional calibrations. By analyzing the lysimeter data from Kimberly, Allen and Brockway (1982) demonstrated that the FAO-modified Blaney Criddle method overpredicted crop water use for the grass reference during the middle of the growing season. Secondly, the standard deviations of evapotranspiration using the estimates from the FAO-modified Blaney Criddle were less than those measured from the lysimeter. Cuenca and Amegge (1987) noted that this second point is important if the predicted evapotranspiration and crop water use pattern is to be applied in probability analysis for irrigation or water resource system design.

The work by Allen and Brockway produced calibrations to adjust the crop water use and standard deviation of evapotranspiration. Table 2 shows the computed monthly adjustment ratios for ETr and standard deviations of evapotranspiration. For the climate conditions at Kimberly, the FAO alfalfa to grass coefficient, i.e.  $ET_{alf}/ET_r$ , should be 1.15 (Doorenbos and Pruitt, 1977). For the middle of the growing season, July through August, Table 2 indicates that the FAO-modified BC method overpredicted grass ETr.

TABLE 2: Monthly Adjustment Ratios for Reference Evapotranspiration and Standard Deviations of Evapotranspiration\*

MONTH	$ET_{alf}/ET_r$	$\sigma_{meas}/\sigma_{calc}$
April	1.21	1.70
May	1.14	1.64
June	1.07	2.70
July	1.01	2.22
August	1.00	2.13
September	1.08	1.61
October	1.22	1.35

\* Taken from Allen and Brockway, 1982.

The correction equation developed by Allen and Brockway for the adjusted monthly grass ETr follows:

$$ET_{r-adj} = ET_r (ET_{alf}/ET_r) / 1.15 \quad (5)$$

where

$ET_{r-adj}$  = adjusted ETr for grass

$ET_r$  = reference evapotranspiration calculated from Eq. (2)

$ET_{alf}/ET_r$  = adjustment ratio from Table 2

The analysis conducted for this thesis did not involve probability analysis of evapotranspiration for irrigation requirements, therefore monthly adjustment ratios for

standard deviations of ET were not used. Calibration for the standard deviation could be accomplished by applying eq. (6). For more information on this calibration, refer to Allen and Brockway (1982) and Allen and Wright (1983).

$$\sigma_{adj} = \sigma_{calc}(\sigma_{meas}/\sigma_{calc}) \quad (6)$$

where

$\sigma_{adj}$  = adjusted standard deviation for ET

$\sigma_{calc}$  = calculated standard deviation for ET

$\sigma_{meas}/\sigma_{calc}$  = adjustment ratio from Table 2

Allen and Brockway (1982) developed an additional calibration to adjust for site aridity. Stations located in completely arid environments tend to have higher temperatures than adjacent stations exposed to the same meteorological conditions but in irrigated environments (Allen et al., 1983). Reference evapotranspiration is supposed to be representative, by definition, of moist, non-arid sites. An equation for an aridity rating was therefore derived to adjust temperature data collected from stations with arid surroundings. The aridity rating is given by the following equation:

$$AR = 0.4(\text{Site } AR) + 0.5(\text{Area } AR) + 0.1(\text{Regional } AR) \quad (7)$$

where

AR = cumulative aridity rating

Site AR = aridity of environment within a 50-m radius of sensor, %

Area AR = aridity of area within a 1.5-km radius of sensor, %

Regional AR = aridity of region within a 50-km radius of sensor, %

The range of the individual aridity ratings is from zero to 100 percent. Zero percent aridity rating represents a completely irrigated environment. Conversely, a 100 percent rating represents a completely arid environment. Application of the aridity factor is discussed in the Methods and Data Selection Section.

### **2.2.2 REGIONAL EVAPOTRANSPIRATION ESTIMATING METHODS**

The scientific community has become increasingly more concerned with the scale in which environmental systems are being examined. Both in the development of water resources for agricultural or other uses and hydrologic modeling, it is required to analyze ET on a regional scale. There are a number of articles describing ET estimates at a local scale and comparisons between the various local ET estimating methods (Doorenbos and Pruitt, 1977; Jensen, 1974; Burman et al., 1983; Allen and Brockway, 1983). However, until recently limited attention has been given to estimating regional evapotranspiration. The work of Morton (1969, 1979, 1978, 1983) concentrated on the analysis of regional ET. Other work was done by Cuenca et al. (1981), Brutseart and Stricker (1979), Seguin (1973, 1975), and Amegge (1985).

Seguin et al. (1982) recommended two main criteria in developing methods for estimating regional ET. The first criteria is to ensure the estimates of ET are representative of the whole surface including the heterogeneity of elementary surfaces making up the regional scale. The second criterion stipulates that the procedure or technique for estimating regional ET must be simple enough to be used for practical purposes given the common network of climatic stations.

The typical approach is to reduce the region into small homogenous units for which local methods may apply, compute the local ET estimate over each homogenous surface, and then take a weighted average of these estimates to represent the region. Other methods have been examined for estimating regional ET. Brutseart and Mawdsley (1976) extended the Penman



aerodynamic method to the planetary boundary layer in estimating regional ET. Rouse and Stewart (1972) described an approach called the equilibrium evaporative approach in which regional ET was approximated by the global radiation term of Penman's equation. Davies and Allen (1973) proposed an extension of the Priestly-Taylor formulation by a parameter dependent on soil moisture conditions.

Recent developments in the technology and techniques of remote sensing have suggested the possibility using remote sensing as a useful tool in improving local and regional evapotranspiration estimates. Much of the technology for collecting the weather and surface parameters needed for ET estimates exists, however the main problem is incorporating remote sensing data with ground-based measurements. Although some resulting formulas offer promising results, their validity has not been adequately verified with respect to soil moisture and cloudy sky conditions to allow operational estimates of regional ETr (Schmugge, 1978; Bernard et al., 1981).

An acceptable method currently practiced in some western states applies local mean monthly estimated ETr to produce contour maps of these estimates. Maps of the entire state of California for each month of the year were recently published. ETr values for approximately 400 sites within California were used to develop detailed isolines for the state (Pruitt et al., 1987). Currently, similar work is being completed in Oregon to develop isolines of mean monthly estimated ETr. In Oregon, the FAO-modified Blaney Criddle method with USDA adjustments was used to estimate ETr at 245 locations. A contouring package, SURFER, was applied to produce the maps of the isolines of ETr.

Amegee (1985) applied geostatistics to regional evapotranspiration. This analysis produced a grid of estimated ETr based on the spatial variability of this parameter as described using geostatistics. The gridded estimates of ETr provided information to develop detailed isolines. Although Amegee (1985) offered promising results, more research was required before geostatistics could be widely used in estimating regional ETr.

## **2.3 FUNDAMENTAL CONCEPTS OF GEOSTATISTICS**

### **2.3.1 OVERVIEW**

At the beginning of the 1960's, G. Matheron (1962-63) built his theory of regionalized variables and proposed a method of estimation called 'kriging'. This method was named after D.G. Krige, who had done some empirical work in South Africa to estimate ore reserve in gold mines. The essence of this theory is that a regionalized variable can be characterized by the correlation between neighboring measurements (Journel and Huijbregts, 1978). This spatial correlation suggests that a value or a sample of some variable is related or correlated in some manner to the value at spatial locations some distance away. This correlation is used to construct a model characteristic of the spatial variation of the desired parameter. This model is used to estimate the parameter at locations where no measurements are available and calculate the error associated with the estimation. Much of the application of regionalized variable analysis was limited to the field of mining. During the last few years, this method has been extended to a large variety of fields including geophysics, meteorology, ecology, geography and oceanography (Henly, 1981). Delhomme (1978) stated that it has proven to be particularly well suited to the problems encountered in hydrosciences. Clark (1979) also emphasized that this estimation technique can be used wherever a continuous measurement is made of a variable at a particular location in space or time i.e. where a sample value is expected to be affected by its position and its relationship with its neighbors.

Geostatistics refers to the application of the theory of regionalized variables to practical problems. Geostatistics has been successfully applied to a number of hydrologic variables because the variation of hydrologic parameters generally has a definable structure (Amegee and Cuenca, 1987). There are two tools applied in geostatistics. The first tool, the variogram, attempts to define the functional form of spatial variation of the variable. The second tool, the kriging systems of equations, applies this defined spatial variation in interpolating the variable

to locations where no data exist. The purpose of the following sections is to present the two main geostatistical tools. The material has been greatly simplified in order to provide at least an initial understanding of the concepts behind geostatistics. A complete derivation of the major principles of geostatistics using evapotranspiration as the regionalized variable can be found in Cuenca and Amegee (1987). For a complete introduction into geostatistics, the following references are recommended: Clark (1979), David (1977), and Journel and Huijbregts (1978).

### 2.3.2 SEMIVARIANCE FUNCTION

The semivariance function attempts to define the variation of the variable, such as evapotranspiration, with respect to distance between known data points. One way to compare two values  $ET(x)$  and  $ET(x+h)$ , separated by distance  $h$ , is to compute their differences. Typically, one is more interested in comparing all the values separated by a given distance  $h$ ,  $n(h)$ . Thus computing the average of the quantity  $[ET(x)-ET(x+h)]$  would be more useful. This computation can be written as follows:

$$D(h) = \frac{1}{n(h)} \sum_{i=1}^{n(h)} [ET(x_i) - ET(x+h)_i] \quad (8)$$

where

$ET(x)$  = evapotranspiration measured at point  $x$

$ET(x+h)$  = evapotranspiration measured at point  $x+h$

$D(h)$  is the estimate of the mathematical expectation of the difference  $[ET(x)-ET(x+h)]$ . A plot of  $D(h)$  for different distances  $h$  is termed the drift.

The drift,  $D(h)$ , can be positive, negative, or zero. But in geostatistics the interest is in the absolute value of the changes as a function of distance. This can be accomplished by

computing means of the absolute values of the changes which can be quite time consuming. Another method is to compute the mathematical expectation of the squared difference of  $[ET(x) - ET(x+h)]$  which is defined as:

$$2\gamma(h) = E \{ [ET(x) - ET(x+h)]^2 \} \quad (9)$$

$2\gamma(h)$  is termed variance function. The semivariance evaluated at distance  $h$  between two measurements is defined as one half of the expected value of the squared difference of  $ET(x)$  and  $ET(x+h)$ . In equation form this becomes

$$\gamma(h) = \frac{1}{2} E \{ [ET(x) - ET(x+h)]^2 \} \quad (10)$$

where

$$\gamma(h) = \text{semivariance for distance } h$$

Converting the expected value notation into computational form, equation (10) becomes

$$\gamma(h) = \frac{1}{(2N(h))} \sum_{i=1}^{N(h)} [ET(x_i) - ET(x+h)_i]^2 \quad (11)$$

where

$$N(h) = \text{number of data pairs of measured evapotranspiration separated by distance } h$$

### 2.3.2.1 Assumptions

A major premise of geostatistics is the ability to define the variation of a random variable as a function of distance. The magnitude of the function characterizing the variation of the random variable may be different from one location to another. However, the mathematical expression of the underlying variability function should be stable over the area of interest. This property is called stationarity. In geostatistics, four possible assumptions can be made.

### First Order Stationarity

The most restrictive assumption is first order stationarity which is met when the mean difference between observations is equal to zero. First order stationarity indicates there is no trend (Clark, 1979) and the variable is homogenous throughout the area of interest. An indicator of the validity of first order stationarity is the drift,  $D(h)$ . If the difference  $D(h)$  is zero for all values of  $h$  over the region considered, the regionalized random variable is said to have first order stationarity (i.e. there is no drift) (Amegee, 1985). The magnitude of deviations of the drift from zero indicates how much the region is heterogeneous with respect to the variable. If there is a trend to the value of the drift as a function of distance, the mean cannot be assumed constant over the domain of analysis (Cuenca and Amegee, 1987). Methods have been developed to deal with the case of a mean which is not stationary but which varies in a regular manner over the domain (David, 1977; Matheron, 1971).

### Second Order Stationarity

This assumption is also termed weak-stationarity and is seldom found in natural phenomena. Two conditions are required in this assumption:

1. The expected value of the regionalized variable  $ET(x)$  is the same over the field of interest;
2. The spatial covariance of the regionalized variable  $ET(x)$  is the same over the field of interest.

The first condition suggests that the expected value of the variable is equal to the mean of the data measured over the region of interest. This condition can be written as follows:

$$E[ET(x)] = m \quad (12)$$

The second condition of second order stationarity implies that for each pair of random variables, the covariance exists and depends on the separation  $h$ . The covariance is defined as the expected value of the product of deviations of two observations from the mean. In its computational form, the covariance is written as follows:

$$C[ET(x), ET(x+h)] = \frac{1}{N(h)} \sum_{i=1}^{N(h)} [ET(x)_i - m][ET(x+h)_i - m] \quad (13)$$

where  $N(h)$  is as previously defined.

The stationarity of the covariance implies stationarity of the variance (Amegee, 1985). Therefore, as the distance  $h$  is reduced to zero, the covariance becomes the variance as shown below:

$$\sigma^2[ET(x)] = \frac{1}{(n-1)} \sum_{x=1}^n [ET(x)_i - m]^2 \quad (14)$$

where  $n$  is as previously defined. Under the hypothesis of first and second order stationarity, there is a constant and finite mean and the covariance and variance exist for the variable of interest. In this case, the semivariance equals the variance minus the covariance, which is given by the following equation (Cuenca and Amegee, 1987):

$$\gamma(h) = \sigma^2[ET(x)] - C[ET(x), ET(x+h)] \quad (15)$$

Second order stationarity suggests there is a known variance and covariance independent of  $x$ . According to Journel and Huijbregts (1978), there are several natural phenomena and random functions which have an infinite capacity for dispersion, i.e. neither have a known variance or covariance, but for which a variogram can be defined. Second order stationarity does not apply if a variance and covariance cannot be defined, as in the case of trends. In this case, a weaker form of stationarity called the intrinsic hypothesis must be assumed.

### **Intrinsic Hypothesis**

For the intrinsic hypothesis, the assumption is that the random variable is not required to have known variance, however the change in the variable should have a definable variance. The intrinsic hypothesis requires that for all distances of  $h$ , the variance of the increments of the function,  $ET(x) - ET(x + h)$ , rather than the function itself, be finite, equal, and independent of position over the field of interest. The semivariance is actually equal to one-half the variance of  $ET(x) - ET(x + h)$ :

$$\gamma(h) = \frac{1}{2} \sigma^2 [ET(x) - ET(x + h)] \quad (16)$$

The semivariance is said to define the spatial structure of the variation of the parameter of interest rather than the spatial structure of the parameter itself (Cuenca and Amegee, 1987).

### **Hypothesis of Universal Kriging**

This last hypothesis is less restrictive than the previous one and assumes the variance of the increments,  $ET(x) - ET(x + h)$ , has some properties of stationarity within a vicinity of restricted size and that the expectation,  $E[ET(x)]$ , which is no longer stationary, varies in a regular manner in such a vicinity (David, 1977). For this hypothesis, the drift term,  $D(h)$ , is not equal to zero, but represents some trend which can be statistically derived by a linear regression technique. This linear regression model of the drift is used in the kriging analysis of the data to account for the drift. More details on universal kriging can be found in David (1977). According to Journel and Huijbregts (1978), quasi-stationarity or the hypothesis of universal kriging is a compromise between data availability and strict stationarity because it is always possible by reducing the vicinity to produce a zone so small that the stationarity is verified. However, Amegee (1985) noted this reduction would not always be possible because of economical constraints related to station density for data collection.

### 2.3.2.2 Properties

A plot representing all the possible values of the semivariance function,  $\gamma(h)$ , as a function of  $h$  is termed a sample variogram. To compute a variogram, one uses Eq. 10 for all possible distances  $h$  which is sometimes called the lag. Through a graphical representation of  $\gamma(h)$  versus lag  $h$ , a curve can be fitted to the cloud of points representing the pairs  $\{h, \gamma(h)\}$ . This curve is referred to as the model variogram. Certain properties of the variogram are discussed in this section. First, the ideal model of the variogram will be explained followed by four common models applied in variogram analysis.

#### Ideal Model

A representation of an ideal variogram is depicted graphically in Figure 2. An ideal variogram is expected to maintain certain properties. As shown in the figure, the semivariance is a positive quantity going to zero as the distance  $h$  goes to zero. Information on the spatial correlation of the variable will be limited to distances greater than the smallest separation between a pair of samples (Cooper and Istok, 1987). Cases in which the range of influence is less than the smallest separation will display a discontinuity at the origin. Sampling and analysis errors also contribute to this discontinuity which is termed the nugget,  $C_0$ .

Also seen in Figure 2, the variogram ideally approaches the variance asymptotically until, at a distance designated the range, it is equal to the variance within some error criteria,  $\Delta$ . This maximum value is termed  $C_s$ . In the presence of a nugget effect,  $C_s$  is equal to  $C_0 + C$ , where the  $C$  term is called the sill value. Conversely, when  $C_0$  is zero, the sill value is equal to the variance. The range,  $a$ , represents the distance beyond which no relationship of the spatial structure for the variable exists.



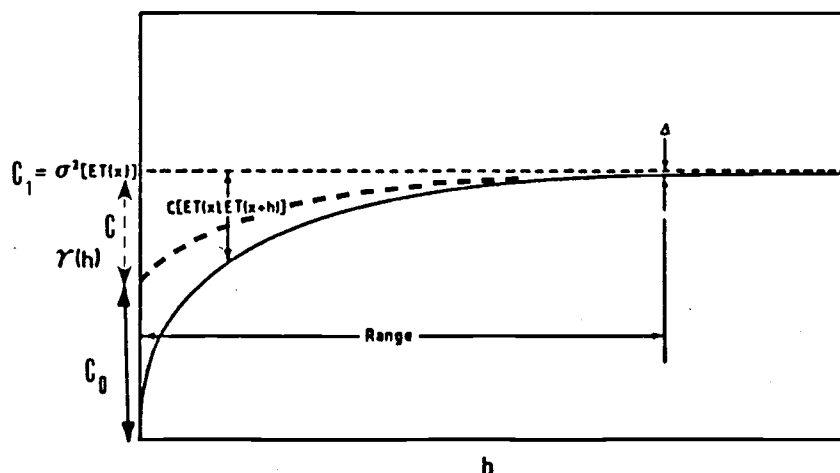


Figure 2: Ideal Variogram

#### Four Common Models

Amegee (1985) commented that no matter how well an model variogram fits the points which represent the computed  $\gamma(h)$ , the model variogram cannot perfectly describe the variability of a natural phenomenon in a region. A variogram can be modeled by any mathematical function as long as it is conditional positive-definite (increasing or constant with increasing  $h$  and nonnegative) (Olea, 1975). However, in practice only four common functions are typically observed and used in geostatistics:

(1) Linear model:

$$\gamma(h) = C_o + b * h \quad 0 \leq h \leq \alpha$$

$$\gamma(h) = C_o + C \quad h > \alpha \quad (17)$$

where  $b$  is the slope

**(2) Spherical model:**

The spherical model is the most commonly used function in geostatistics. David (1977) noted that it has been possible to estimate a hundred ore deposits with only the spherical and exponential model and the tendency is to use only the spherical model. The mathematical form of this model is written as follows:

$$\begin{aligned}\gamma(h) &= C_o + C \left[ \frac{3}{2} \left( \frac{h}{a} \right) - \frac{1}{2} \left( \frac{h}{a} \right)^3 \right] & 0 \leq h \leq a \\ \gamma(h) &= C_o + C & h > a\end{aligned}\tag{18}$$

where

$C_o$  = nugget effect

$C$  = variance of the random variable

$a$  = range of influence of the semivariance function

**(3) Exponential model:**

$$\begin{aligned}\gamma(h) &= C_o + C \left[ 1 - \exp \left( - \left( \frac{h}{a} \right) \right) \right] & 0 \leq h \leq a \\ \gamma(h) &= C_o + C & h > a\end{aligned}\tag{19}$$

**(4) Gaussian model:**

$$\gamma(h) = C_o + C \left[ 1 - \exp \left( -3 \frac{h^2}{a^2} \right) \right]\tag{20}$$

**Isotropic and Anisotropic**

A variogram model can be isotropic or anisotropic. If all the variograms represent identical models regardless of the direction of  $h$ , the variogram is termed isotropic. Therefore, the spatial correlation depends only on the distance of  $h$  and not the direction.

It follows that when the variogram is a function of the direction of  $h$ , the variogram is anisotropic. When the variogram is anisotropic, a variogram must be determined for each direction of isotropic. Two types of anisotropy have been identified in geostatistics, geometric and zonal (Amegee, 1985).

### 2.3.3 KRIGING

Kriging is the interpolation technique of geostatistics which makes optimal and unbiased estimates of regionalized variables at unknown locations using the structural properties of the variogram and known data values. There are two types of kriging : simple, ordinary, and universal. Simple and ordinary kriging are applied for the case of second order stationarity and the intrinsic hypothesis. Simple kriging assumes that local means are relatively constant and equal to the mean of the data. Ordinary kriging assumes the local means are not closely related to the mean of the data. In the case of a drift or nonstationarity, universal kriging is the technique applied. These types of kriging have two forms of estimation, point or block. Point estimation refers to estimation of the variable, such as  $ET(x)$ , at a single location. Block estimation is performed by applying the interpolation technique of the mean value of  $ET(x)$  over a block portion of the region of interest.

The following sections presents the governing equations, constraints, and kriging system of equations for the case of ordinary point kriging. Details on universal kriging can be found in David (1977). As mentioned before, the following material has been greatly simplified. A complete derivation of the kriging system of equations with evapotranspiration as the regionalized variable can be found in Cuenca and Amegee (1987).

### 2.3.3.1 Governing Equation

The governing equation for estimating a variable at an unmeasured point using kriging is based on a linear condition. The kriging estimate for a variable at an unknown location is represented by a linear combination of measured data at surrounding locations, each measured value receiving different weights. Therefore, the closer a neighboring point is to the desired point, the more heavily its value is weighted when the unknown values are estimated. The governing equation can be written as:

$$ET^*(x_p) = \lambda_1 ET(x_1) + \lambda_2 ET(x_2) + \lambda_3 ET(x_3) + \dots + \lambda_n ET(x_n) \quad (21)$$

where

$ET(x_p)$  = kriging estimate of evapotranspiration at point  $x_p$

$ET(x)$  = measured value of evapotranspiration at point  $x$

$\lambda_i$  = weight assigned to each measured value

To minimize computing costs, in practice  $n$  is limited to only the number which lie closest to the point at which  $ET^*(x_p)$  is being estimated (Cuenca and Amegee, 1987). The assigned weights applied to each measured value is determined using two constraints required to derive the kriging system of equations coupled with the variogram.

### 2.3.3.2 Constraints

The two conditions used to compute the weights are:

1. Unbiasedness: The mean of the kriging estimates is equal to the mean of the observed data.

2. Best criterion: The variance of the error between the kriging estimate and the true value is minimized.

The unbiased condition may be expressed as

$$E[ET^*(x)] = E[ET(x)] = m \quad (22)$$

$$E[ET^*(x)] = \frac{1}{n} \sum_{i=1}^n \lambda_i ET(x_i) = m \sum_{i=1}^n \lambda_i \quad (23)$$

The result of applying an unbiased condition is that the sum of the individual weights must be equal to 1. This result is obtained by combining Eqs. (22) and (23):

$$\sum_{i=1}^n \lambda_i = 1 \quad (24)$$

The second condition, the best criterion, states that the variance of the estimation error be minimized. This condition is written as follows:

$$\begin{aligned} \sigma^2[\epsilon_p] = \sigma^2[ET(x_p)] - 2 \sum_{i=1}^n \lambda_i C[ET(x_p), ET(x_i)] + \\ \sum_{i=1}^n \sum_{j=1}^n \lambda_i \lambda_j C[ET(x_i), ET(x_j)] \end{aligned} \quad (25)$$

Eq. (25) must be solved for those weights  $\lambda_i$  which minimize the estimation variance under the constraint that the sum of the weights be equal to 1.

### 2.3.3.3 Kriging System of Equations

The kriging system of equations results from applying the previous conditions to Eq. (25) in an attempt to solve for the weights. To minimize Eq. (25), it is necessary to take the derivative with respect to the weights. In doing so, one realizes the need to introduce a Lagrangian multiplier,  $-2\mu$ , to rectify the situation of having  $n + 1$  equations for  $n$  unknowns (Cuenca and Amegge, 1987). The final result is the following kriging system of equations:

$$\begin{aligned}
\lambda_1 \gamma(h_{11}) + \lambda_2 \gamma(h_{12}) + \dots + \lambda_n \gamma(h_{1n}) + \mu &= \gamma(h_{1p}) \\
\lambda_1 \gamma(h_{21}) + \lambda_2 \gamma(h_{22}) + \dots + \lambda_n \gamma(h_{2n}) + \mu &= \gamma(h_{2p}) \\
&\vdots \\
&\vdots \\
\lambda_1 \gamma(h_{n1}) + \lambda_2 \gamma(h_{n2}) + \dots + \lambda_n \gamma(h_{nn}) + \mu &= \gamma(h_{np}) \\
\lambda_1 + \lambda_2 + \dots + \lambda_n + 0 &= 1.0
\end{aligned} \tag{26}$$

The  $\gamma(h)$  in Eq. (26) are determined from the variogram thus allowing the unknown weights  $\lambda_i$  to be solved. The resulting,  $\lambda_i$ , are used in Eq. (21) with measured values of evapotranspiration to produce the kriging estimate of evapotranspiration at the unmeasured location,  $ET^*(xp)$ . As concluded by Cuenca and Amegee (1987), the kriging system of equations is said to result in the best-linear-unbiased estimate.

### 3 METHODS AND DATA SELECTION

The state of Oregon was selected as the geographic base. A project conducted by the Water Resources Engineering Team of the Department of Agricultural Engineering at Oregon State University was recently completed to produce revised estimates for consumptive use and net irrigation requirements for Oregon. Much of the methods and data analysis from this project were incorporated into this thesis. This chapter describes the available weather data, choice of the ETr estimating method, determination of the five climatic regions, and geostatistical programs applied in analyzing the ETr data.

#### 3.1 CHOICE OF EVAPOTRANSPIRATION METHOD

The FAO-Modified Blaney Criddle Method was chosen as the estimating method for the revision work and this thesis. As mentioned in the Literature Review, the studies performed in Washington, Idaho, and Oregon suggested that this would be the best temperature-based method to use. The decision to use this empirical method was based upon known availability of temperature data throughout Oregon. The data required by the FAO-modified Blaney Criddle are broken into primary weather parameters and secondary weather parameters. These two types of data are discussed in the following section.

A computer program, CROP MIR, was written in QuickBASIC to compute the evapotranspiration estimate along with the net irrigation requirements of specific crops during the revision project performed by the Water Resources Engineering Team. The subprogram BLACRI calculated the ETr. It was used in this project to estimate ETr at 180 locations given the following input data: monthly average maximum and minimum daily temperatures ( $T_{max}$  and  $T_{min}$ ), monthly minimum relative humidity ( $RH_{min}$ ), ratio of actual to maximum possible sunshine hours ( $n/N$ ), daytime average windspeed at 2 m height ( $U_{day}$ ), latitude, longitude, and elevation. The output of this subprogram was ETr estimates for each month and location

where weather station data were available. For this thesis, ETr estimates during 1985, 1986, and 1987 for May through September at 180 weather stations were calculated and used in the geostatistical analysis. A listing of the subprogram BLACRI is in Appendix C.

## **3.2 AVAILABLE WEATHER DATA**

### **3.2.1 PRIMARY WEATHER DATA**

The primary weather data consisted of monthly averages of daily maximum and minimum air temperature. Kelly Redmond, State Climatologist, provided the monthly averages of daily maximum and minimum air temperature recorded by the various weather stations throughout the state of Oregon. 180 primary stations had the required air temperature data for the given months in the three years studied. Appendix A gives the listing of the primary weather stations chosen for this work. Figure 3 shows the distribution of these stations throughout the state.

### **3.2.2 SECONDARY WEATHER DATA**

The secondary weather data required to estimate ETr by the FAO-modified Blaney Criddle method include long-term monthly averages of minimum relative humidity, ratio of actual to maximum possible sunshine hours, and daytime average wind speed at 2 m height. These data were available from a number of different sources for a limited number of weather stations. Figures 4, 5, and 6 show the location of the weather stations providing the secondary weather data. A detailed examination of the secondary data sources for each station was made. The source chosen was based on the length of recorded data and ease of obtaining and processing the information.



# WEATHER STATIONS FOR THE STATE OF OREGON

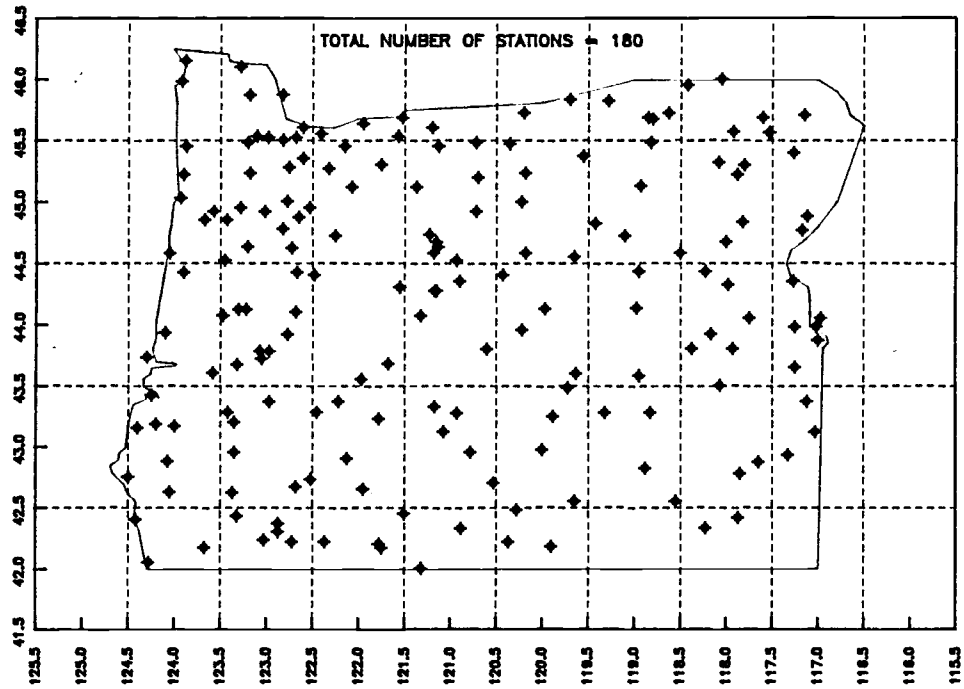


Figure 3: Primary Weather Stations for Oregon

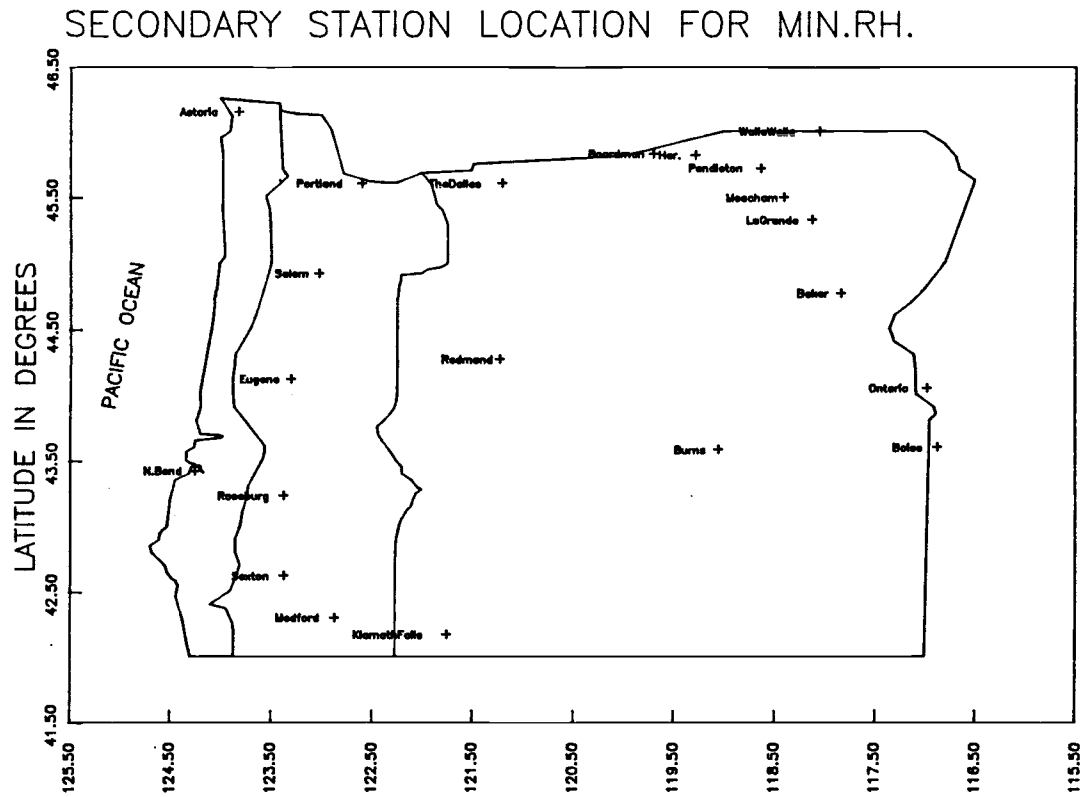


Figure 4: Location of Weather Stations giving RHmin

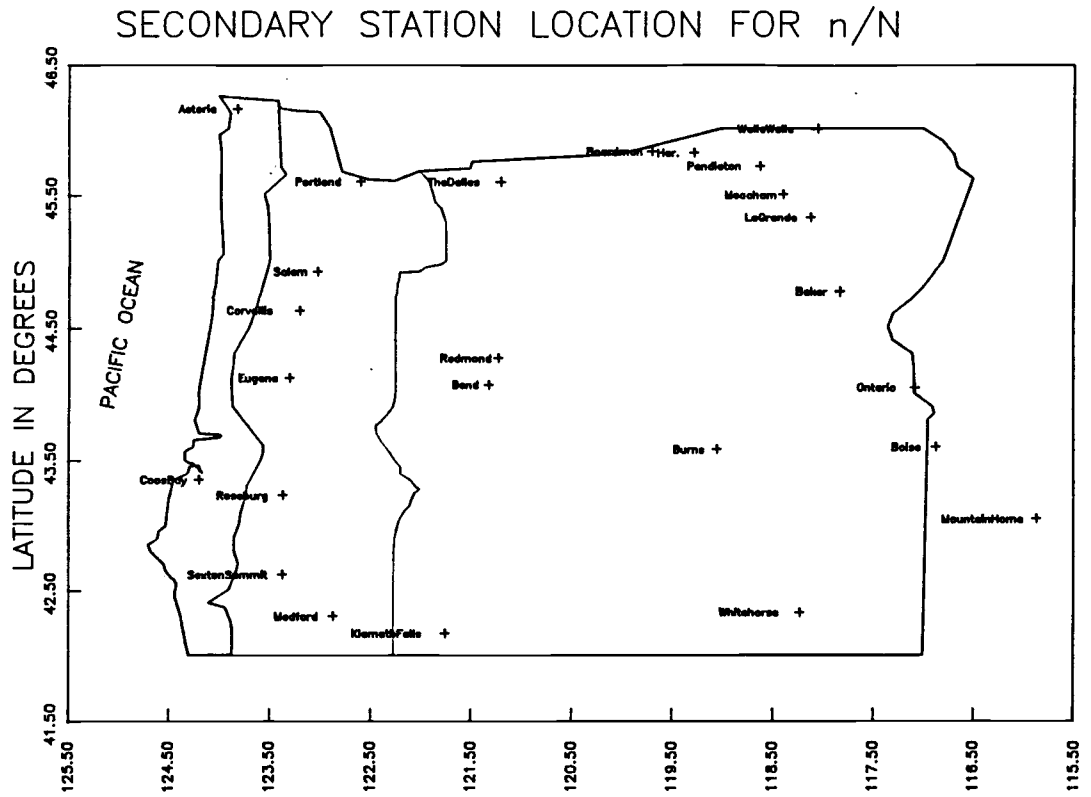


Figure 5: Location of Weather Stations giving  $n/N$

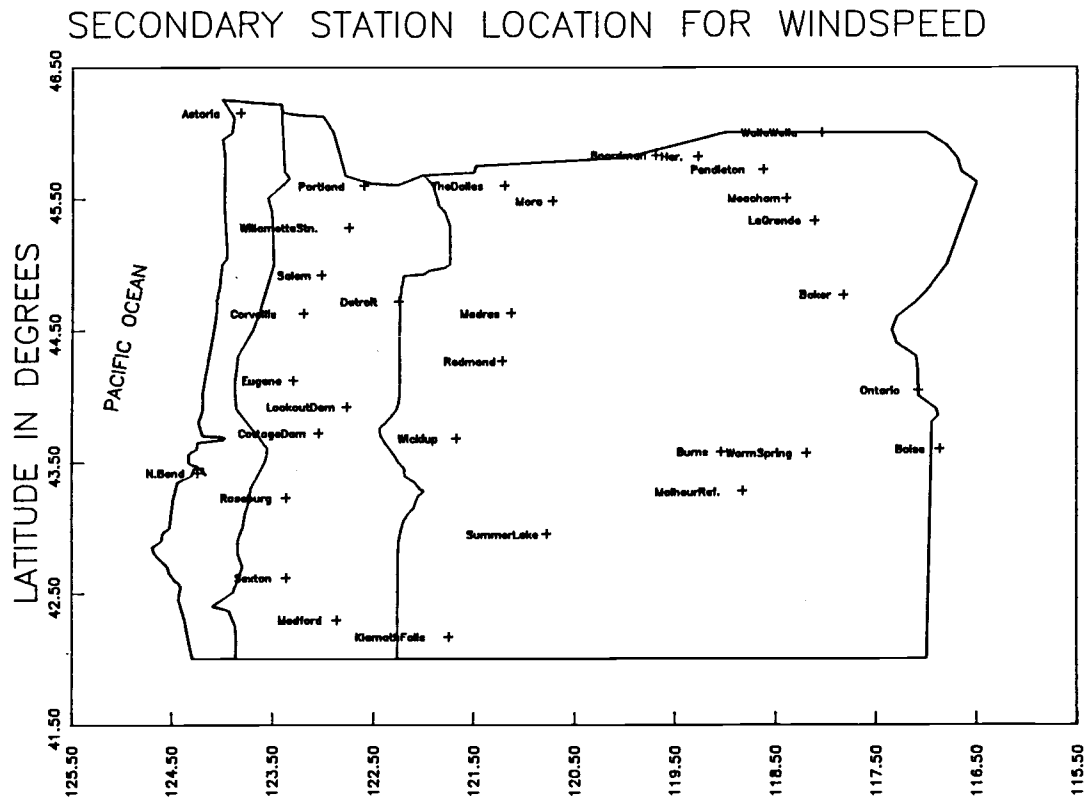


Figure 6: Location of Weather Stations giving windspeed

For the minimum relative humidity, 21 weather stations were identified. Appendix B lists the stations used, the different sources giving information on minimum relative humidity at each station, and the data source used in the final analysis. Stations providing dewpoint temperature were employed with an empirical relationship between dewpoint temperature and air temperature to estimate minimum relative humidity. The following equation represents that relationship (Cuenca, 1989):

$$RH_{\min} = 100 \frac{\{112 - 0.1(T_{\max}) + T_{dp}\}}{\{110 + 0.9(T_{\max})\}} \quad (27)$$

where

$T_{\max}$  = maximum temperature, °C

$T_{dp}$  = dewpoint temperature, °C

The ratio of actual to maximum possible sunshine hours ( $n/N$ ) was available at 25 weather stations. The stations and the associated sources giving information on  $n/N$  are listed in Appendix B including the data source used in the analysis. Stations with cloud cover information were utilized by applying the relationship described in FAO 24 (Doorenbos and Pruitt, 1977) to get  $n/N$ . Below is the relationship between cloudiness and the  $n/N$  ratio.

cloudiness(tenths)	0	1	2	3	4	5	6	7	8	9	10
$n/N$ ratio	.95	.85	.8	.75	.65	.55	.5	.4	.3	.15	

Stations with incoming shortwave solar radiation information employed the following equation to estimate  $n/N$ :

$$n/N = [Rs / (0.5)Ra] - 0.5 \quad (28)$$

where

$R_s$  = incoming shortwave solar radiation, mm/d

$R_a$  = atmospheric solar radiation, mm/d (Table 2, Doorenbos and Pruitt, 1977, FAO 24, pg. 9 and 12)

Daytime windspeed at 2m height was available at 32 stations. Appendix B provides a list of the stations used, the different sources giving information on daytime windspeed at each station, and the data source used in the final analysis. Some of the stations had to be adjusted to 2m height using Eq.(4) as discussed in the Literature Review section.

Once  $RH_{min}$ ,  $n/N$ , and windspeed were determined at the 21, 25, and 32 weather stations, respectively, interpolation of these values to the primary station locations was required. For this procedure, Oregon was divided in three zones: 1) coast, 2) Willamette and Southwestern Valleys, and 3) east of the Cascades. Stations with secondary data in each of these zones were used to interpolate the secondary parameters to the primary weather stations in the same zones. A computer program, INTER.BAS, was written to perform the interpolations. This program employed an inverse distance technique such that the influence of a data point declines with a weighting power of distance. In this case, an inverse square distance method was chosen. A search radius of 192 km (120 miles) was used to ensure that at least every primary location had one secondary location to interpolate the secondary values.

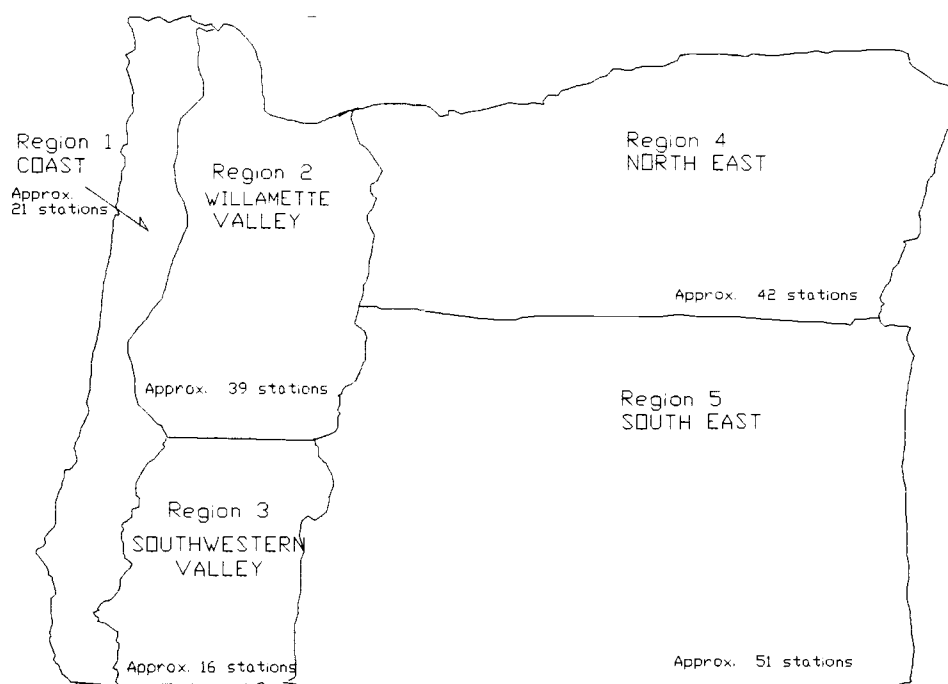
### 3.2.3 ARIDITY FACTORS

To perform the USDA adjustments discussed in the Literature Review, information on the site, area, and region of the weather station was required. Descriptive information of the

station location and its surroundings was obtained through a personal visit with Clint Jensen (National Weather Service, Portland, Oregon). Aridity factors were subjectively made for the site, area, and region based on the information provided by Mr. Jensen. Cumulative aridity was computed using equation (7) described in the Literature Review section. The cumulative aridity rates provide an adjustment to the air temperature data in arid surroundings. A listing of the site, area, region, and cumulative aridity rates for each station are in Appendix A.

### **3.3 CLIMATIC REGIONS FOR ANALYSIS**

The state of Oregon was divided into five climatic regions based on topographic features and local meteorological conditions: 1) Coastal, 2) North intermountain valley, 3) South intermountain valley, 4) North high plateau, and 5) South high plateau (Amegee, 1985). Figure 7 shows the five climatic regions for the state of Oregon. Looking at a topographic map of Oregon, the most noticeable features are two north south mountain ranges, the Coastal and Cascade ranges, the valley resting between the two mountain ranges, and the high plateau and highlands east of the Cascades. West of the Cascades, the climate is humid with an average annual precipitation of approximately 1000 millimeters (40 inches) in the intermountain valleys. East of the Cascades, the climate is semi-arid to arid with an annual precipitation of approximately 250 millimeters (10 inches) or less.



**Figure 7: Division of Climatic Regions for the State of Oregon**

The five climatic regions were the basis for the regions used in the geostatistical analysis. The 180 weather stations were separated into their respective regions. Appendix A includes a listing of the name, location, and region of each weather station.

To reveal the variability of evapotranspiration between regions, the average ETr in the regions for each month were plotted in Figure 8. The plot indicates distinct differences in estimates of evapotranspiration between certain regions.



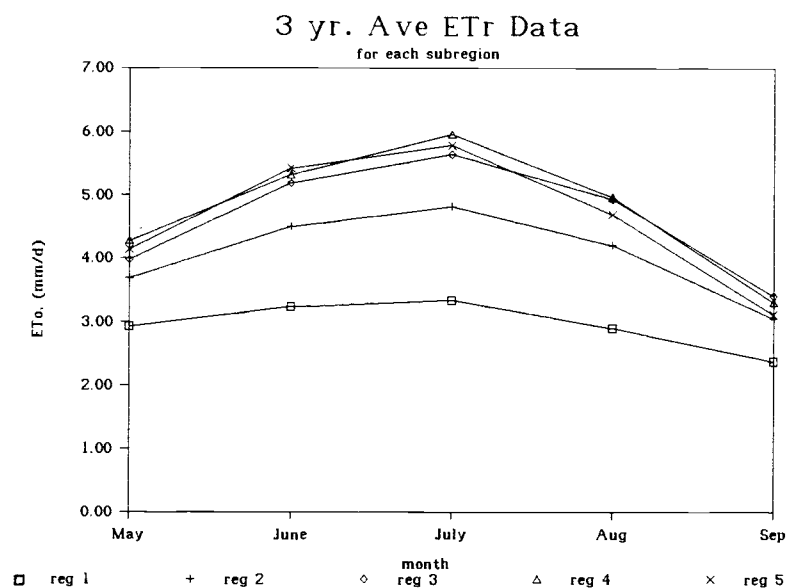


Figure 8: ETr Plot for Each Climatic Region

### 3.4 COMPUTER PROGRAMS FOR GEOSTATISTICAL ANALYSIS

A search for available geostatistical application programs was made at the start of this work. It was desired to utilize a package which provided variogram analysis, cross validation, kriging, and contour mapping routines in a user friendly environment.

The software chosen for this work was developed by the Environmental Protection Agency (EPA), in cooperation with the Applied Earth Sciences Department at Stanford University and the Computer Sciences Corporation. Geo-EAS (Geostatistical Environmental Assessment Software) is a collection of interactive software tools for performing two-dimensional geostatistical analyses of spatially distributed data. The program is menu driven and provides data file management, data transformations, univariate statistics, variogram analysis, cross validation, kriging, contour mapping, post plots, and line/scatter graphs.

The program VARIO in Geo-EAS was used to compute the semivariance functions and to model the sample variograms. The cross validation procedure was performed by the XVALID program in Geo-EAS. The kriging program KRIGE in Geo-EAS was used to estimate regional ETr at points on a grid representative of the individual regions. The contouring package used was SURFER from Golden Software. This contouring package proved to be more useful than the contouring program provided in Geo-EAS.

## **4 PROCEDURE FOR GEOSTATISTICAL ANALYSIS**

The geostatistical analysis involved data preparation, variogram modeling, cross validation, kriging and mapping the estimates of ETr. An outline of each step of the procedure was discussed in the first section of this chapter. The sections following indicate details of data preparation, variogram modeling, cross validation, kriging and mapping of the ETr estimates.

### **4.1 PROCEDURE FOR ANALYSIS**

The procedure applied consisted of the following steps:

1. Inspect the data using STAT1 from Geo-EAS. Each data set was checked for outliers and statistical information such as the mean, standard deviation, and sample variance was calculated. The outliers in the data were determined and removed. This procedure is discussed in detail in Section 4.2.

2. Following verification of the data set, the semivariance functions were calculated and plotted, using VARIO, to visualize the sample variogram. A model variogram was fitted to the data. The details of the variogram modeling are discussed in Section 4.3.

3. The model variogram was cross validated using XVALID. The cross validation results were checked with the criteria established for each region to determine if the model variogram was an acceptable model. If the model failed, another model variogram was tested until an acceptable model was found or it was determined that no variogram could be fit to the data. The details of the cross validation procedure are discussed in Section 4.4.

4. Once the model variograms were determined for the average ETr data in each month and region, the models were tested in the individual years (1985, 1986, and 1987). The cross validation procedure was performed for the individual years to check the results of using the model variograms from the average ETr applied to the three individual years.

5. The final step in the geostatistical procedure was kriging and contouring the ETr estimates. Using the KRIGE subroutine in GeoEAS and the model variograms for the average ETr data, kriging was done for two months (July and September) of the three year average ETr data in each region. The details on kriging and contouring the ETr data are discussed in Section 4.5

## **4.2 DATA PREPARATION**

The initial step of the data preparation was preparing the Geo-EAS ASCII data files. A detailed description of the format is discussed in the user's guide for the Geo-EAS software available through the Environmental Protection Agency (EPA). The monthly data (May through September) furnished for 1985, 1986, and 1987 in each region were used to calculate a three year average of the ETr data. Geo-EAS files were created for the three year average ETr data along with the ETr estimates for the individual years. A data file consisted of ETr estimates provided at the weather stations available in the specific region for a particular month.

Previous research on reference evapotranspiration had already documented that this parameter was a probability variable with a normal distribution (Wright and Jensen, 1972; Nixon et al., 1972). Cuenca (1989) commented that if enough years of daily data are available, the daily evapotranspiration rate can be shown as normally distributed, thus implying the monthly evapotranspiration is also normally distributed. Since reference evapotranspiration was already known to represent a normal distribution, there was concern that possible outliers existed in the data sets. The final step in the data preparation was to explore the ETr estimates looking for outliers which were unrepresentative of the data set. STAT1 provided in Geo-EAS was utilized to produce the normal probability plots of the data. A probability plot is a cumulative frequency plot scaled so that a normal distribution plots as a straight line. By

examining the normal probability plots, data points which unquestionably did not lie on the line through the plotted points were identified as outliers and removed from the data set. Once the outliers were removed, the data sets were ready for the variogram analysis.

### **4.3 VARIOGRAM MODELING**

The core of geostatistical analysis is in the computation, interpretation, and modeling of the variogram. The variogram attempts to interpret the spatial structure between neighboring variables or measurements, and controls the way the kriging weights are designated to known data points used in interpolating at unknown locations. There are several interpolating and contouring methods which assume that a measurement at any point represents nearby locations better than locations further away. These methods employ an arbitrary weighting factor as a function of distance for the interpolation of the variables to unknown locations. The difference between these methods and geostatistics is that the variogram analysis in geostatistics strives to quantify the spatial relationship of the variance between data points in order to determine the weighting factors.

As seen in Eq. (10), a plot of the semivariance function depicts one half the squared difference (or variance) of the pairs of measurements relative to the distances separating the pairs. The plot of the semivariance function is called the sample variogram. In practice, the semivariance function is calculated for groups of measurement pairs in class intervals of similar distances and direction (Englund and Sparks, 1988). Using a graphical plot of the variances versus distances for a particular direction, a model variogram is fitted through the plot.

Using VARIO from Geo-EAS, the semivariance functions were calculated and plotted with respect to distances separating the pairs of data. Since the regions used for the analysis were assumed to be homogeneous, a variogram for the region regardless of direction was desired. The direction option from the VARIO analysis consisted of the direction and angular tolerance.

tolerance. Figure 9 illustrates how these settings affect the grouping of pairs within a lag interval. For this work a zero direction with a 90 degree angular tolerance was used. These settings allowed all pairs to be included regardless of direction and maximized the number of pairs in each distance class. The lag intervals used in the geostatistical analysis were determined from a rule of thumb which states that variograms are generally not valid beyond one half the maximum distance between samples (Geo-EAS, 1988). In the VARIO program, the maximum pair distance is divided by two and then subdivided into ten equal distance classes. The above settings used in the analysis were the default values given in VARIO routine of Geo-EAS.

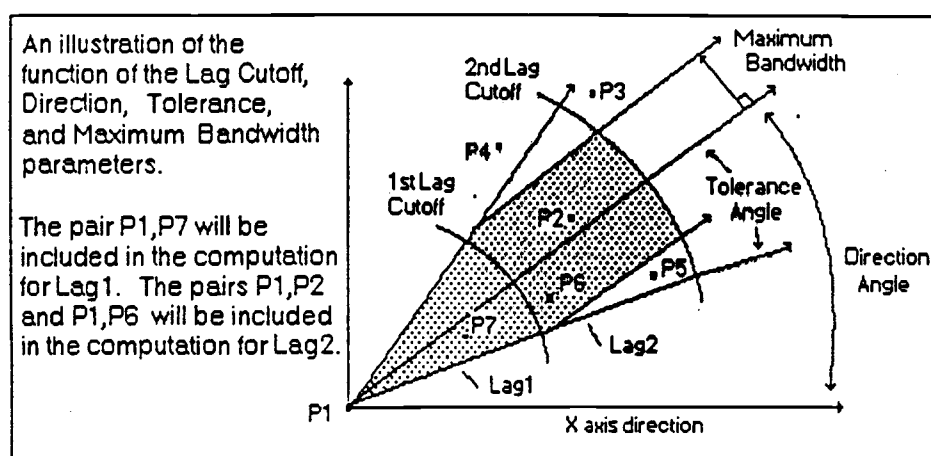


Figure 9: Illustration of Direction Parameters (taken from user guide of Geo-EAS)

From the plotted graph of the variances versus distances, a model variogram was fitted through the data. As discussed in the Literature Review section, four models are commonly

most commonly selected variogram model for applications in hydrology, this model was used. To fit a spherical model to the variogram, three parameters needed to be visually estimated from the plot. The three parameters consisted of the nugget ( $C_0$ ), sill ( $C$ ), and range ( $a$ ). A modeling option in VARIO allowed the user to estimate these parameters and visually see how the model variogram fitted the data. The best model is selected subjectively by picking the model that appears to have the best fit and at the same time satisfies the quantitative error criteria which is checked in the analysis.

#### 4.4 CROSS VALIDATION

Delhomme (1976) proposed a cross validation procedure to determine the best model variogram when ambiguity exists in the model selection. The procedure consists of removing the known variables from the data set one at a time and kriging the remaining known variables to estimate the value at the location of the removed variable. In the cross validation procedure suggested by Delhomme (1976), the model variogram is tested against certain conditions to judge the acceptability of the variogram. These conditions determine if there is a bias in the estimates, if the estimation errors are consistent with the kriging variances, and if the model is an optimal model.

The first condition requires testing the variogram to ensure unbiased estimates and consistency. To be unbiased, the average kriging error (AKE) must close to zero:

$$AKE = \frac{1}{n} \sum_{i=1}^n [ET^*(x_i) - ET(x_i)] = 0 \quad (29)$$

where

$ET^*(x_i)$  = kriged evapotranspiration at  $x_i$

$ET(x_i)$  = observed or measured evapotranspiration at  $x_i$

$n$  = number of measurements of evapotranspiration over the region of interest

For the kriging errors to be consistent with the kriging variances, the standardized error should be normally distributed with a mean close to zero and a variance close to one (Delhomme, 1976). The mean and variance of the standardized errors can be written as follows:

a) mean of standardized error:  $m_{se} = 0$

$$m_{se} = \frac{1}{n} \sum_{i=1}^n \{ET^*(x_i) - ET(x_i)\} / \sigma_{ki} \quad (30)$$

where  $ET^*(x_i)$ ,  $ET(x_i)$ , and  $n$  are previously defined and  $\sigma_{ki}$  is the kriging standard deviations.

b) variance of standardized error:  $s_{se}^2 = 1 \pm 2\sqrt{\left[\frac{2}{n}\right]}$

$$s_{se}^2 = \frac{1}{n-1} \sum_{i=1}^{n-1} \{[ET^*(x_i) - ET(x_i)]^2\} / \sigma_{ki}^2 \quad (31)$$

where  $\sigma_{ki}^2$  is the kriging variances.

The second condition requires determining if the model variogram is optimized by finding the model with the minimum mean squared error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^n [ET^*(x_i) - ET(x_i)]^2 = minimum \quad (32)$$

As a practical rule, the MSE should be less than the variance of the sample values (Cooper, 1986):

$$MSE < \sigma^2 \quad (33)$$

where  $\sigma^2$  is equal to the variance of the sample values,  $ETr$ . As commented by Cooper (1986), if the MSE is less than the sample variance, the kriging estimate is an improvement over the estimate provided by the mean for all the sample values. It follows that the root mean square error (standard deviation of the kriging errors) should be lower than the standard deviation of



the regionalized variable, ETr. Table 3 shows the criteria specified for each region from the cross validation conditions described. The number of stations is approximate since this number varied from month to month within a region.

Table 3: Cross Validation Criteria for each region

Region	n approx	$S_{ee}^2$	$m_{ee}$	AKE	Standard Deviation: Error Variable
1	21	$1 \pm 0.6172$	0.00	0.00	$S_{error} < S_{var}$
2	39	$1 \pm 0.4529$	0.00	0.00	$S_{error} < S_{var}$
3	16	$1 \pm 0.7071$	0.00	0.00	$S_{error} < S_{var}$
4	42	$1 \pm 0.4364$	0.00	0.00	$S_{error} < S_{var}$
5	51	$1 \pm 0.3961$	0.00	0.00	$S_{error} < S_{var}$

The cross validation procedure provides a good method of checking whether the model variogram meets the validation criteria. However caution is required not to assume the model variogram is a valid model only because these conditions are satisfied. The cross validation criteria are necessary but not sufficient conditions for an acceptable model variogram. The last and most important of the criteria in this procedure is that the validated model variogram also closely approximates the sample variogram of the data (Clark, 1986; Journel and Huijbregts, 1987).

#### 4.5 KRIGING AND MAPPING EVAPOTRANSPIRATION DATA AND ERROR

Kriging and mapping ETr was performed on the average reference evapotranspiration data for 1985, 1986, and 1987. Two types of kriging were possible in the KRIGE routine in Geo-EAS: simple and ordinary. Using the validated model variogram obtained from the cross validation procedure along with the KRIGE routine in the Geo-EAS package, ordinary kriging

was performed for two months (July and September) in each region. These two months were chosen to give an illustration for the middle and end of the growing season. In the kriging analysis, ETr was estimated using the weights solved by the kriging system of equations at points of a specified grid superimposed over the region. The kriging standard deviations for the kriged ETr estimates at the grid points were also computed in the KRIGE routine. This standard deviation gives an estimate of the error associated with the kriged ETr estimates.

The KRIGE routine in the Geo-EAS package provides a grid option used to specify the origin of the grid, the size of grid cells, and the number of cells in the X and Y direction. The size of grid cells indicates the distance between points in the grid. The number of cells chosen determines the number of points to be produced in each of the two directions. For each of the regions, the grid spacing chosen was 10 km by 10 km. Amegee (1985) chose a grid size of 12.87 km (8 miles) based upon the fact it has been customary to assume that at distances greater than 16.5 km (10 miles) from a weather station, adjustments may need to be made to ET estimates in order to take into consideration the variability due to distance, surface heterogeneity, and micro-climatic modifications. Since the analysis performed in this work was on a subregional scale, it was decided to reduce the grid size to 10 km to allow smaller regions to have an adequately dense grid of the kriged ETr estimates.

For the mapping of the kriged estimates of ETr and standard deviations, a contouring software package, SURFER, was utilized. The gridded information on kriged ETr and standard deviation for regions providing validated model variograms was imported into SURFER along with a boundary file representing the outline of the region. The SURFER package was used to draw isolines through the gridded information along with an outline of the region.

## **5 RESULTS AND DISCUSSION**

This chapter presents results obtained from analysis of monthly reference evapotranspiration (ET<sub>r</sub>) estimates for the regions representing the state of Oregon. The first two sections discuss data analysis and preparation which preceded the geostatistical analysis. Following these sections, results of the variogram and cross validation analysis, outcome of using model variograms obtained from average ET<sub>r</sub> estimates as the model variograms for the ET<sub>r</sub> estimates in the individual years, and kriging and mapping the kriged ET<sub>r</sub> along with the error associated with the kriged estimate are discussed. Alternate notation for reference evapotranspiration (ET<sub>o</sub>) given by Doorenbos and Pruitt (1977) was used in certain figures presented in this chapter. In any case, the reference crop is always grass.

### **5.1 SAMPLE VARIANCE**

The sample variance was calculated for each data set. A data set consisted of ET<sub>r</sub> estimates for a particular month and region in a given year or average of the three years. Table 4 presents the sample variances calculated for each data set. The sample variances were used to determine a reasonable maximum value of the model variogram. As indicated in the Literature Review, by definition the sample variance is theoretically the maximum value of the sample variogram.

TABLE 4: Sample Variance of ETr for each month for each year in each region

	May	June	July	August	September
Region 1:					
1985	0.0350	0.0456	0.109	0.0490	0.0387
1986	0.0436	0.0635	0.0462	0.1106	0.0460
1987	0.0556	0.0388	0.0510	0.0836	0.0348
3 yr Ave	0.0331	0.0513	0.0629	0.0707	0.0243
Region 2:					
1985	0.0846	0.0487	0.0677	0.0572	0.0301
1986	0.0640	0.0395	0.0751	0.0506	0.0280
1987	0.0786	0.0556	0.0726	0.0723	0.0377
3 yr Ave	0.0747	0.0453	0.0681	0.0561	0.0390
Region 3:					
1985	0.3290	0.4570	0.2435	0.2570	0.1484
1986	0.3273	0.4486	0.3280	0.3276	0.1360
1987	0.3326	0.4706	0.2733	0.3213	0.0827
3 yr Ave	0.3241	0.4600	0.2636	0.3293	0.1164
Region 4:					
1985	0.1573	0.2709	0.1086	0.1055	0.1002
1986	0.1216	0.1252	0.0784	0.1043	0.0763
1987	0.1543	0.2508	0.0817	0.2152	0.0712
3 yr Ave	0.1510	0.1420	0.0728	0.1458	0.1089
Region 5:					
1985	0.2960	0.3850	0.3702	0.1613	0.1127
1986	0.1984	0.4134	0.4186	0.1890	0.1248
1987	0.2681	0.3083	0.3983	0.1728	0.1314
3 yr Ave	0.1857	0.3424	0.4481	0.1601	0.1361

## 5.2 DATA PREPARATION

The first step in data analysis is to become familiar with the data set. This includes exploring distributions of the data throughout the area of interest, computing the statistics of the data, and observing other characteristics. As discussed in the Procedure section, the data used in this project were examined for outliers which were unrepresentative of the data sets. The procedure for locating these outliers consisted of investigating normal probability plots of the data. Figure 10 provides an example of a normal probability plot from the average ETr estimates for August in region 1. One can see from the plot that an outlier exists for this data

set (i.e. one data point clearly does not lay on the straight line representing a normal distribution of the data). Any data values representing outliers, such as seen Figure 10, were removed from their respective data sets.

An example of a data set not showing outliers can be seen in Figure 11. This figure represents the normal probability plot for the average ETr estimates for September in region 5. As seen in the figure, the data are normally distributed along a straight line.

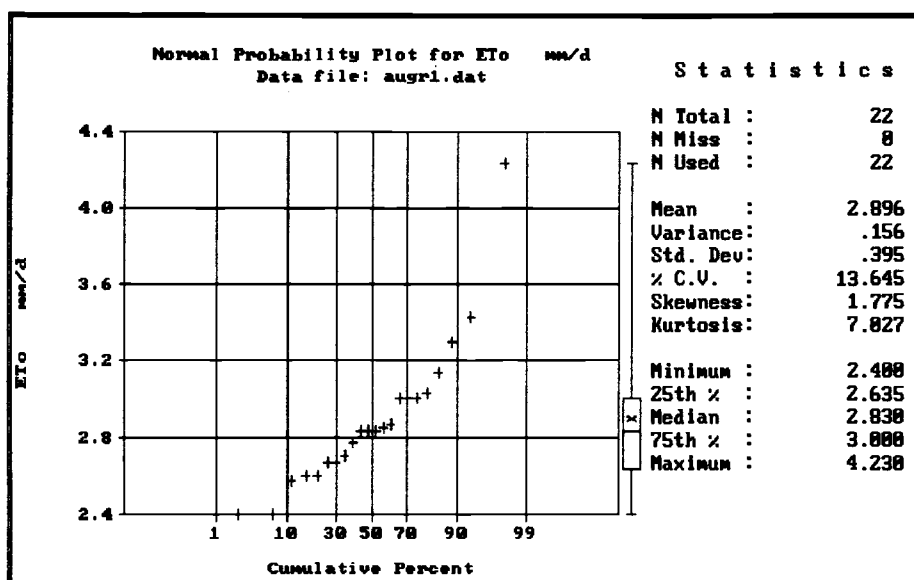


Figure 10: Normal Probability Plot for Ave. ETr in August, Region 1

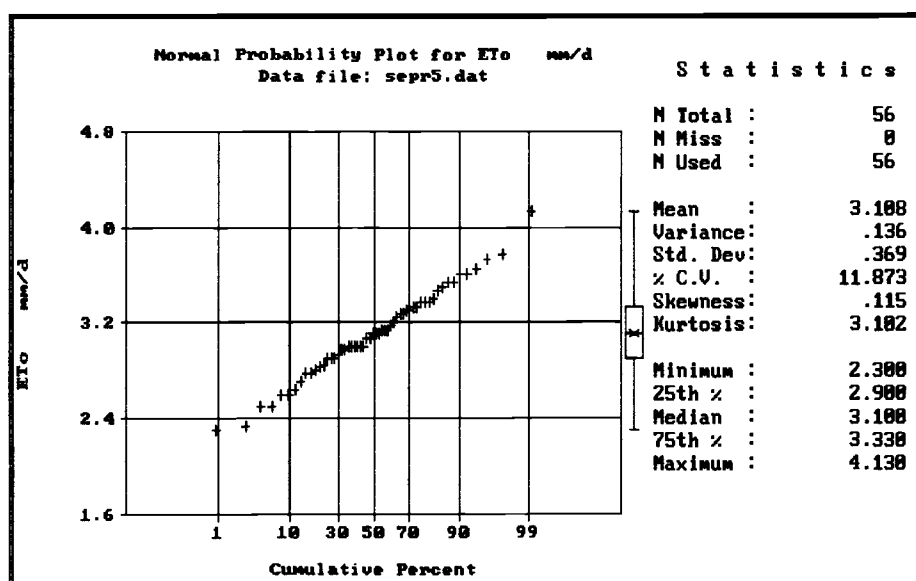


Figure 11: Normal Probability Plot for Ave. ETr in September, Region 5

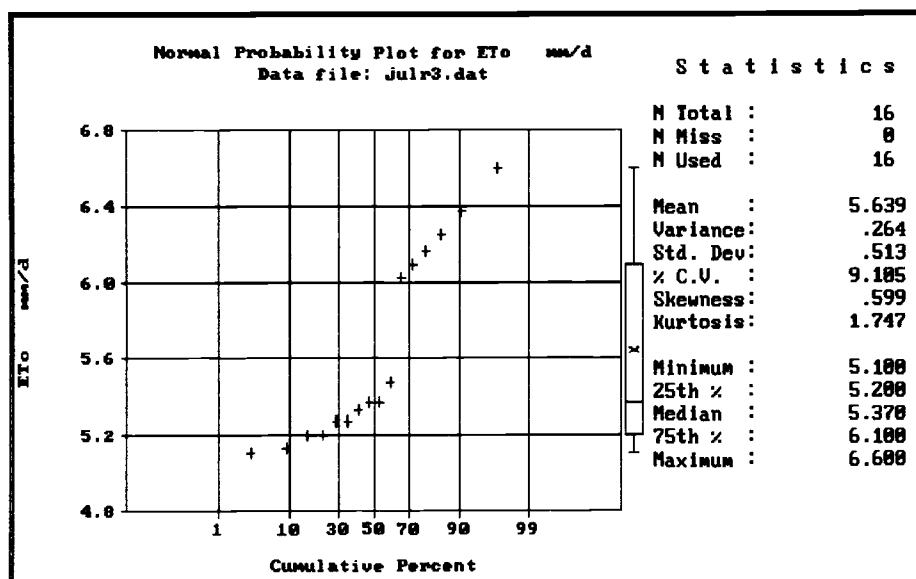


Figure 12: Normal Probability Plot for Ave. ETr in July, Region 3

Normal probability plots for four out of five regions showed the data to be normally distributed and outliers were easily identified. The region not representing a normal distribution for the data was region 3. Figure 12 is the normal probability plot for July in region 3. Since from previous research ETr is known to be normally distributed, this plot suggests that not enough data points exist to adequately define the distribution. Devore and Peck (1986) commented that normal probability plots from small sample sizes can have substantial departures from a straight line even when the distribution is normal. The plot might also suggest region 3 should be divided into two regions. A closer examination into the location ETr estimates falling along the two apparent lines could aid in this decision. Region 3 remained in the geostatistical analysis, but it was anticipated that this region would not yield good results.

### **5.3 VARIOGRAM/CROSS VALIDATION RESULTS**

Sample variograms were calculated for each month and region. Using the modeling option provided in VARIO, model variograms were fitted to the sample variograms. Model variograms were first subjectively fit through the cloud of points representing the sample variograms and then tested by the cross validation procedure. The model variogram selected was that which satisfied the criteria established in the cross validation procedure and which appeared to best fit the sample variogram. The model variograms selected to fit the sample variograms for each month and region are shown in Figures 13 through 17. The X axis in these figures represent the distances,  $h$  in km, separating the data pairs used to calculate the semivariance function. The results of the cross validation analysis for these models are found in Table 5. It should be noted that the sample variances shown under parameters in the figures are not always representative of the actual sample variance. A bug in the Geo-EAS program is considered the reason for this error.

The spherical model was selected as the model variogram to be used based on its wide application in hydrology. In general, the sample variograms for the different regions and months within the regions exhibited the characteristics of a spherical model. There were some cases that the sample variogram represented what is called a pure nugget model. However, spherical models were still used in these cases because it was assumed that had there been more data pairs to compute the first point on the sample variogram, the variogram could be represented by a spherical model. For some regions, there was considerable variability seen in the sample variograms. One of the expected reasons for this variability was the lack of enough samples to represent the spatial distribution of the data adequately. This was particularly noticable in region 3.

As discussed earlier, the spherical model requires visualizing the nugget ( $C_0$ ), sill ( $C$ ) and range ( $a$ ) from the sample variogram. The sample variance was calculated to help define the possible maximum value of the sample variograms. For four out of five regions, the maximum value of the sample variograms approached the sample variance. However, this is not a requirement of a valid sample semvariogram. Only the model variograms representing the sample variograms in region 5 had a maximum value less than the sample variance.

Since the nugget is associated with the error of the estimation or measurement of the variable at a point and there are known errors related to the reference evapotranspiration estimate, one would expect to see evidence of a nugget effect. For regions 1 and 3, it was difficult to discern a nugget in the sample variogram, therefore a zero nugget was used in the spherical model. If there had been a way to know the estimation errors associated with the FAO-modified Blaney Criddle method, a minimum value for the nugget could have been stipulated. The other three regions (2, 4, and 5) showed a nugget effect due to the expected error of the estimates. Within these three regions, the nugget was not constant for every



month. One would not necessarily expect the nugget to be constant. The fact that each month did not always have the same number of ETr estimates and the varying magnitude of this estimate could explain this shifting nugget.

The range of the spherical model represents the limit of influence of the sample variogram. At distances greater than the range, geostatistics provides no relationship for the spatial structure of the variable. One could also remark that the range gives an indication of the distance the estimates of ETr obtained at a weather station influences ETr within the region. There was not a fixed pattern in the variation of the range by month for each region. In general, the range started with a low value in May, increased during the warmest part of the growing season, and then decreased to a low value again in September. There were certain anomalies in the range with large variations between months, particularly in region 4. There is no clear reason for this anomaly. The final range selected was the value which best satisfied the cross validation criteria.

The results of the cross validation of the model selected for each month within the individual regions are given in Table 5. For four out of five regions, the selected models met the criteria of the cross validation tests. The values for the averaged kriged error (AKE) and mean of the standardize error ( $m_{se}$ ) in region 3 are larger (i.e. diverge more from zero) than those obtained in the other regions. Therefore, it was difficult to confirm that the model variograms for this region were valid. From the distinct disparity seen in the normal probability plots and the small sample size of this region, it was not surprising that variograms were not able to be modeled to the data. This region was eliminated from the kriging and mapping of the ETr.

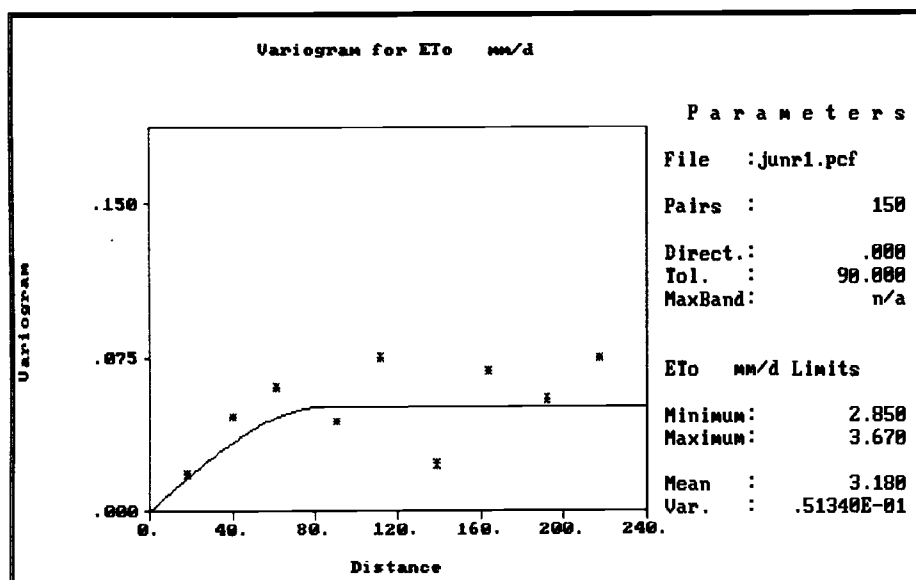
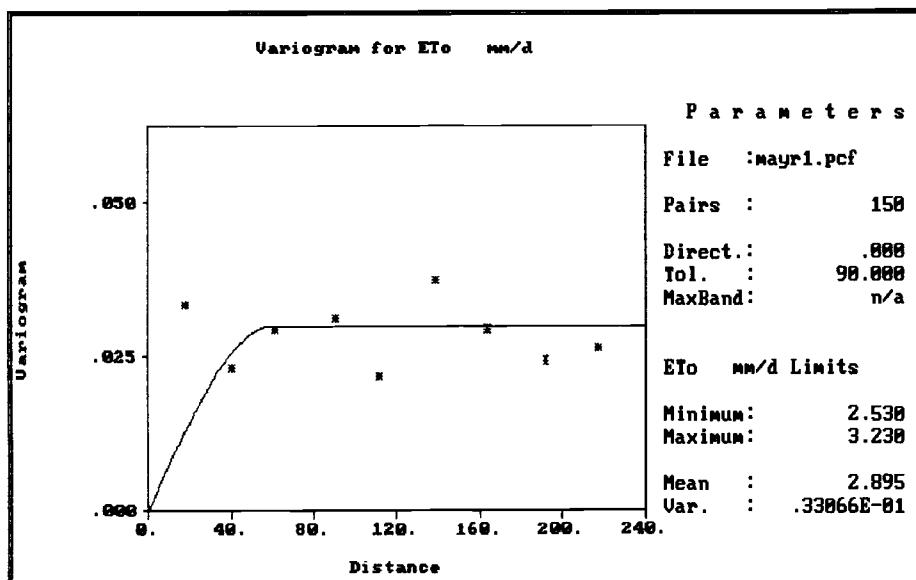


Figure 13: Variograms for Region 1

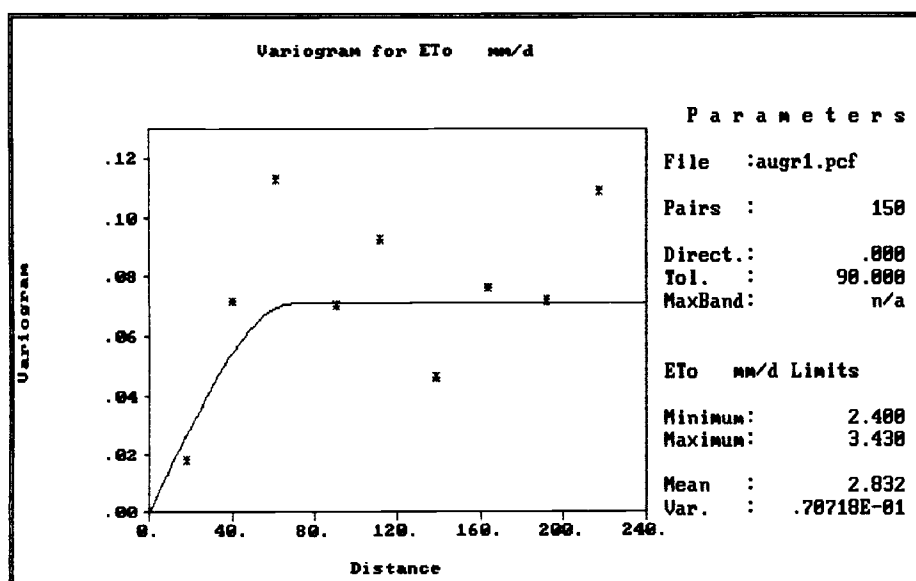
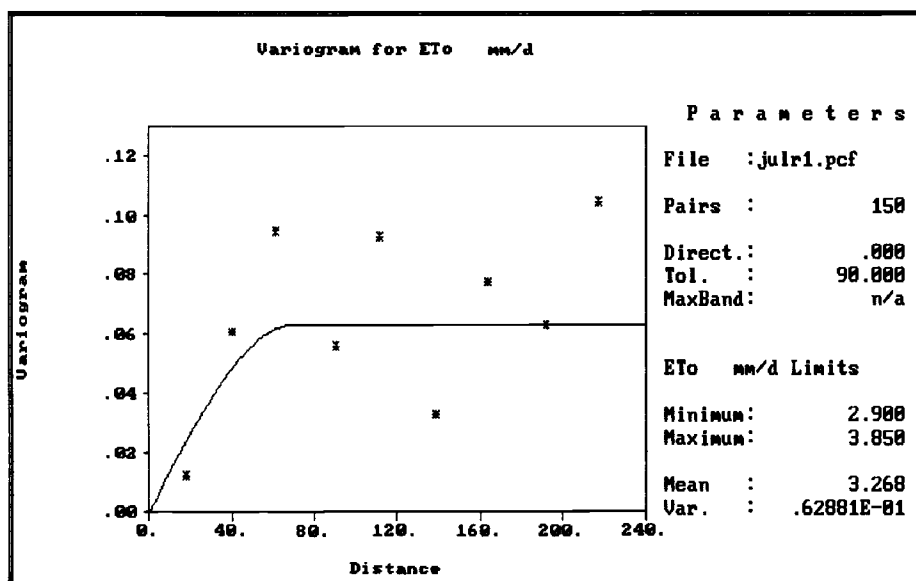


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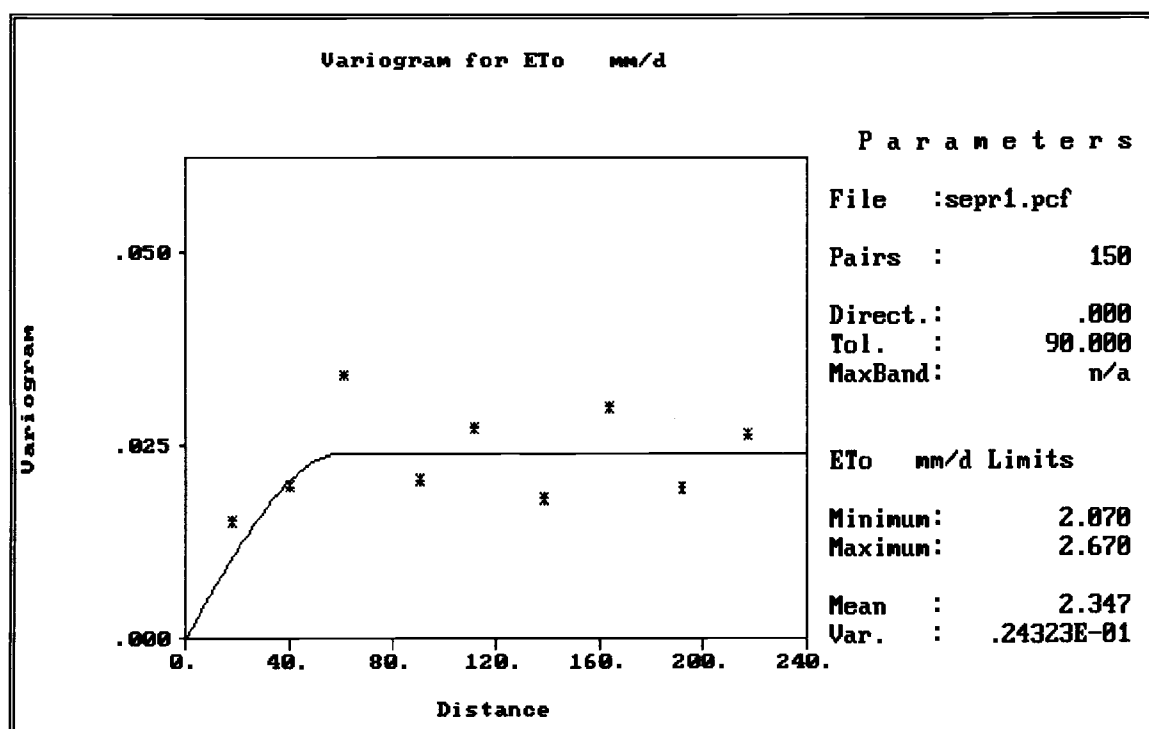


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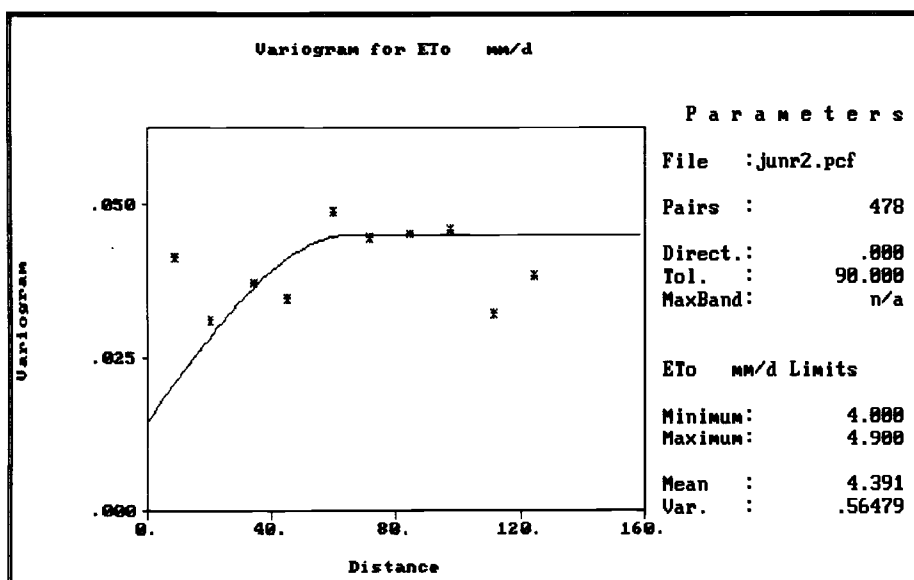
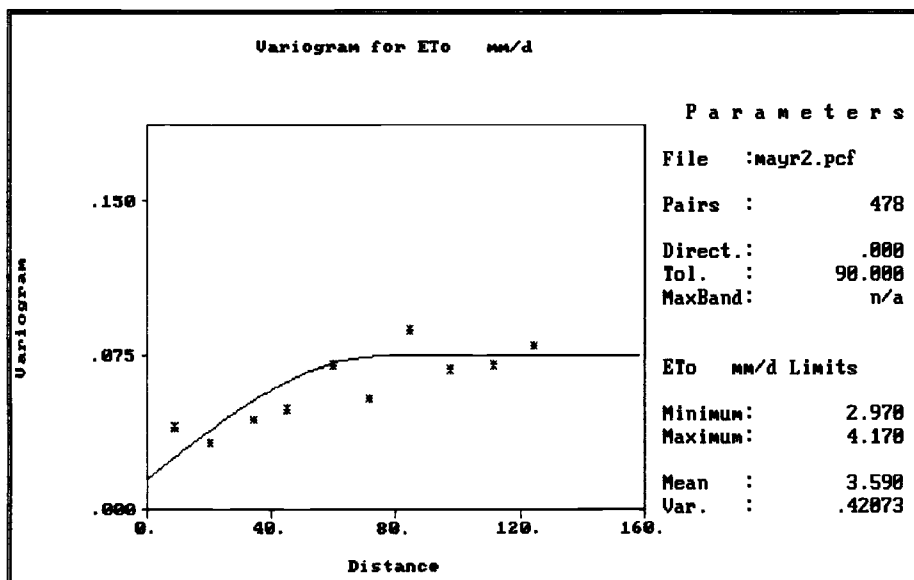


Figure 14: Variograms for Region 2

Semi

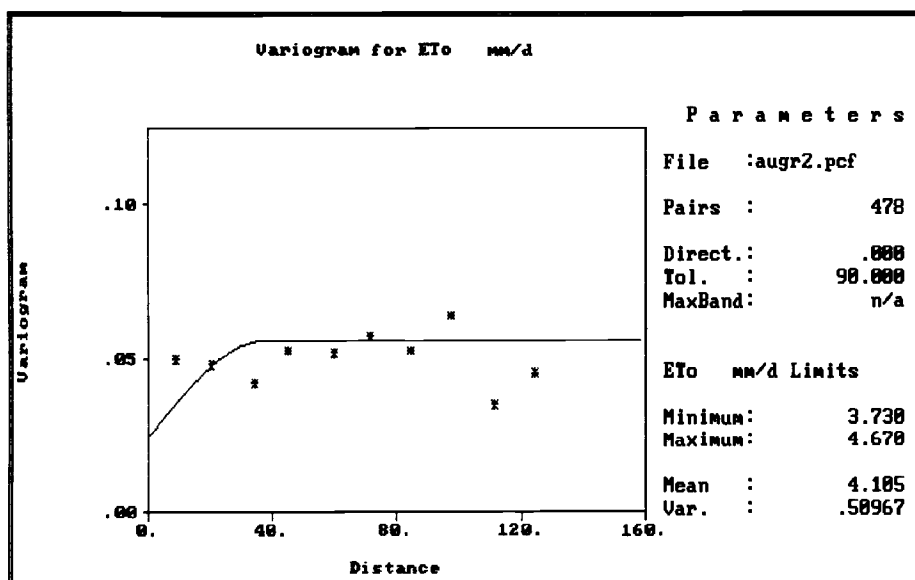
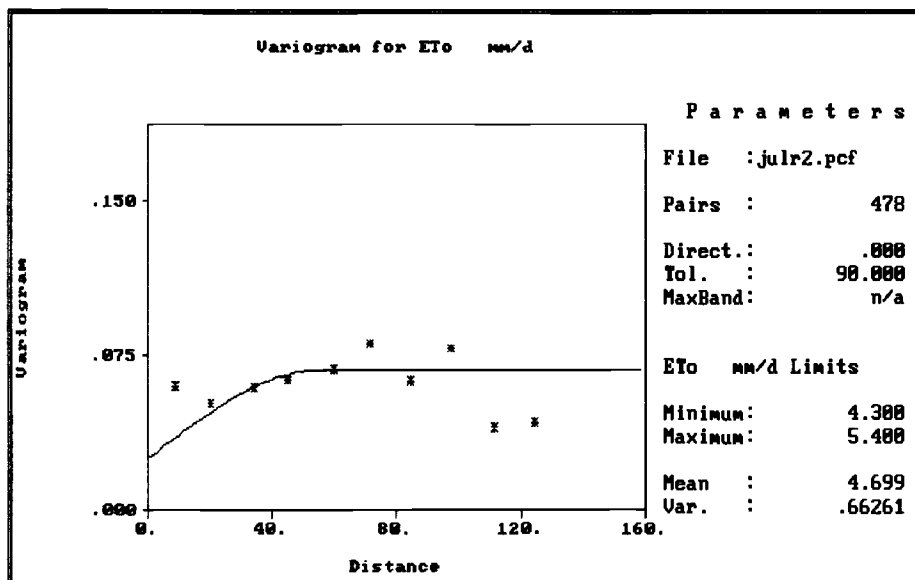


Figure 14: cont.

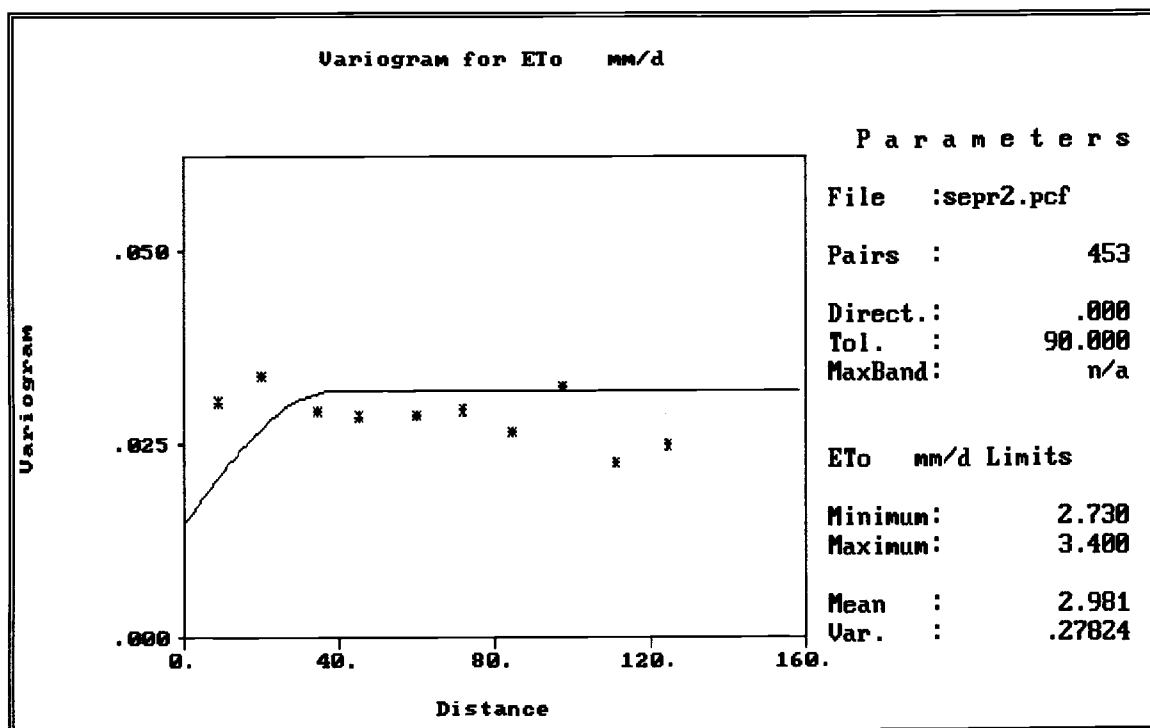


Figure 14: cont.

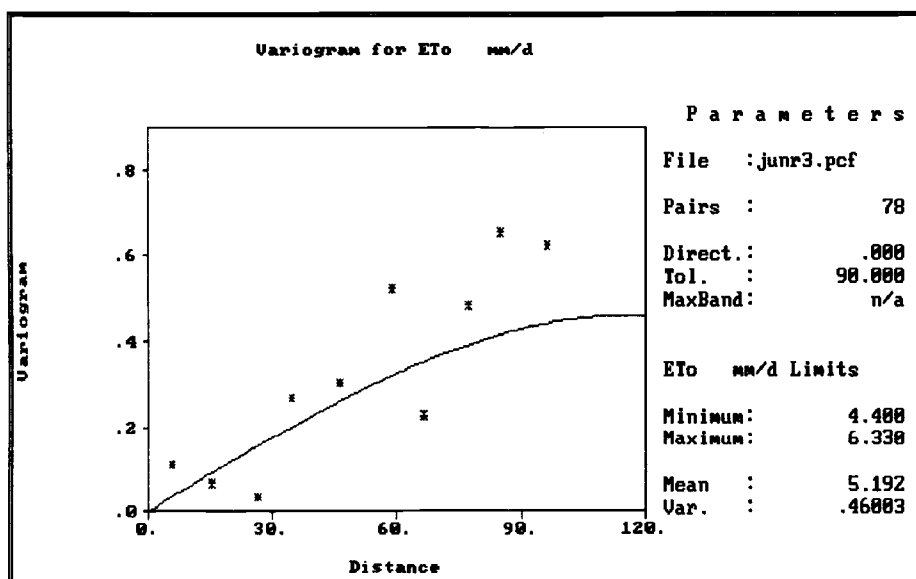
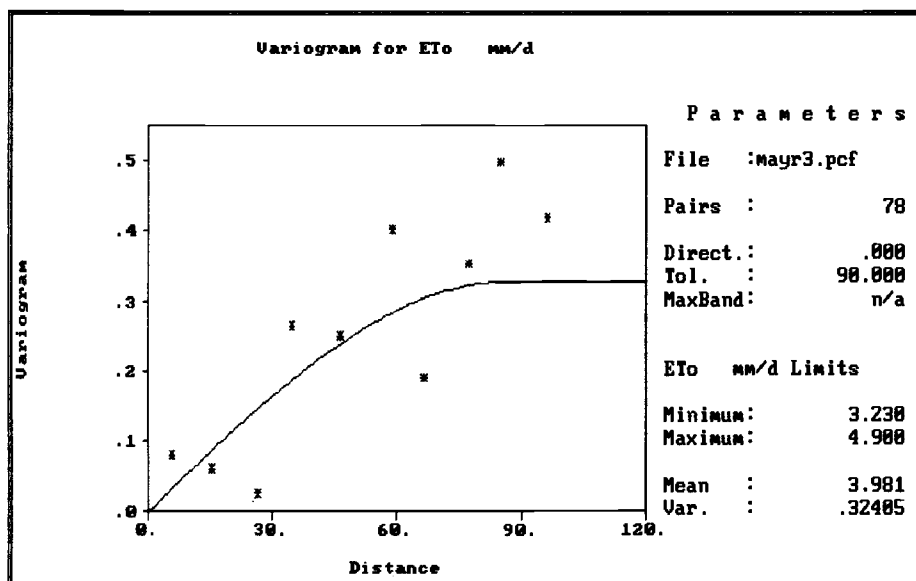


Figure 15: Variograms for Region 3

semi



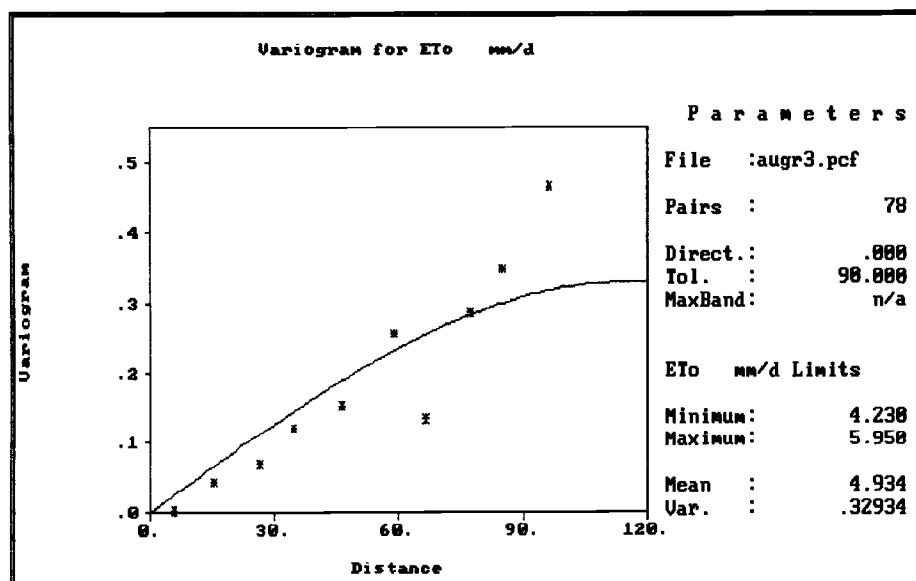
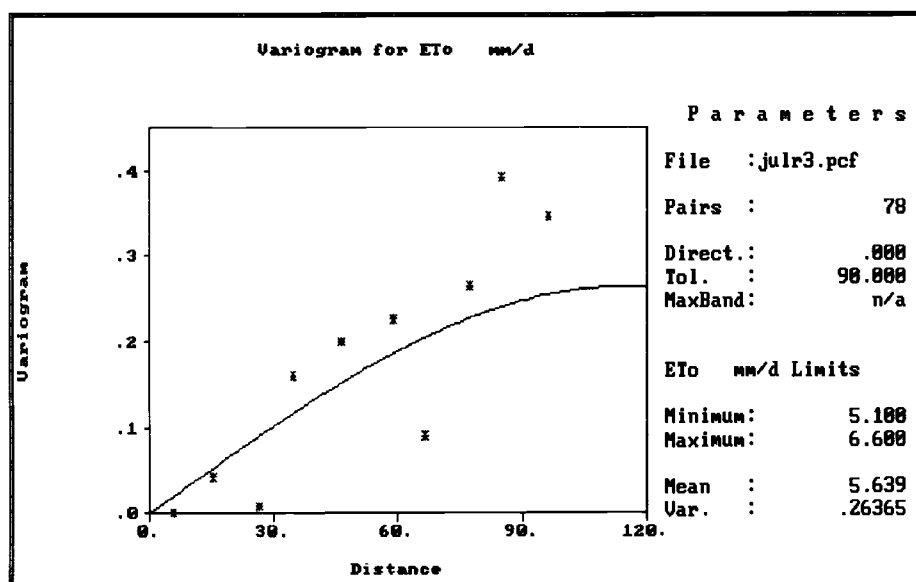


Figure 15: cont.

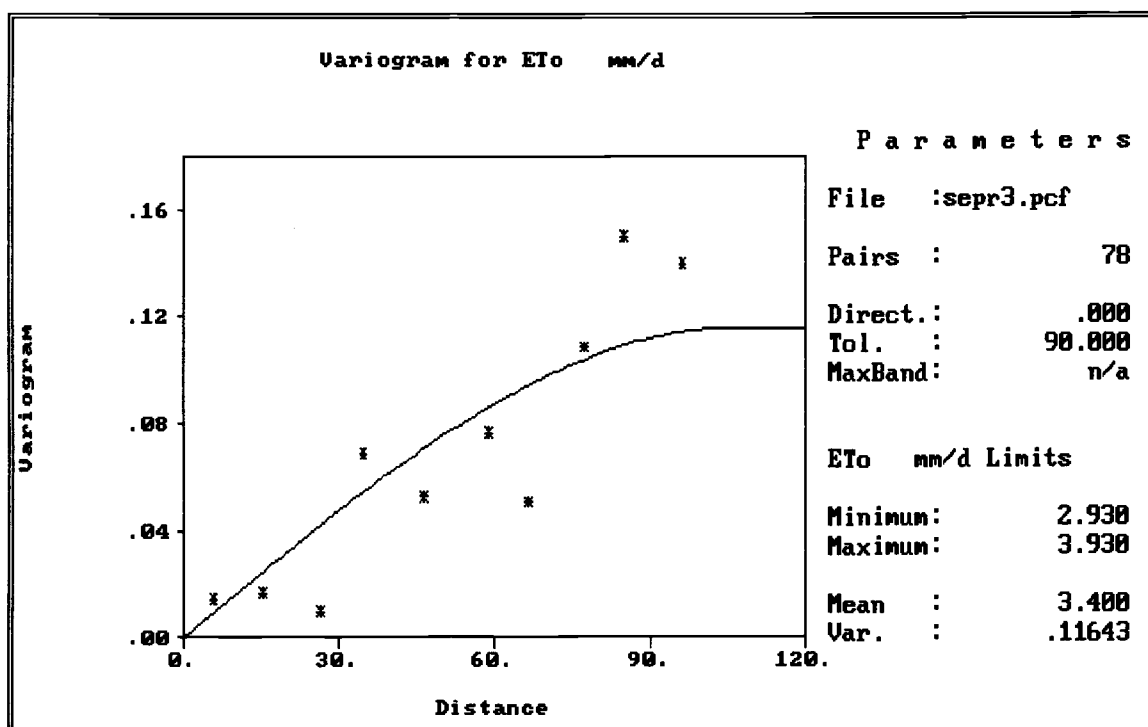


Figure 15: cont.

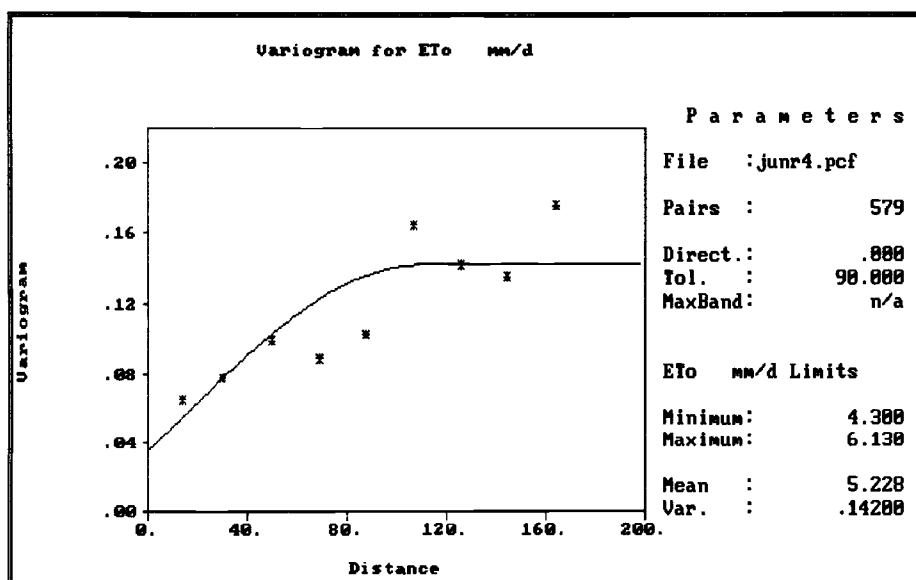
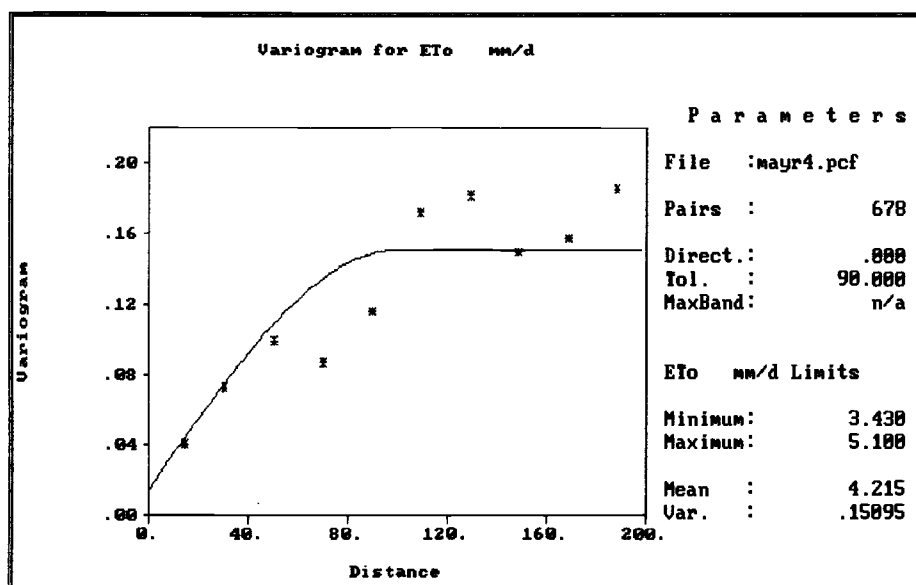


Figure 16: Variograms for Region 4

Semi

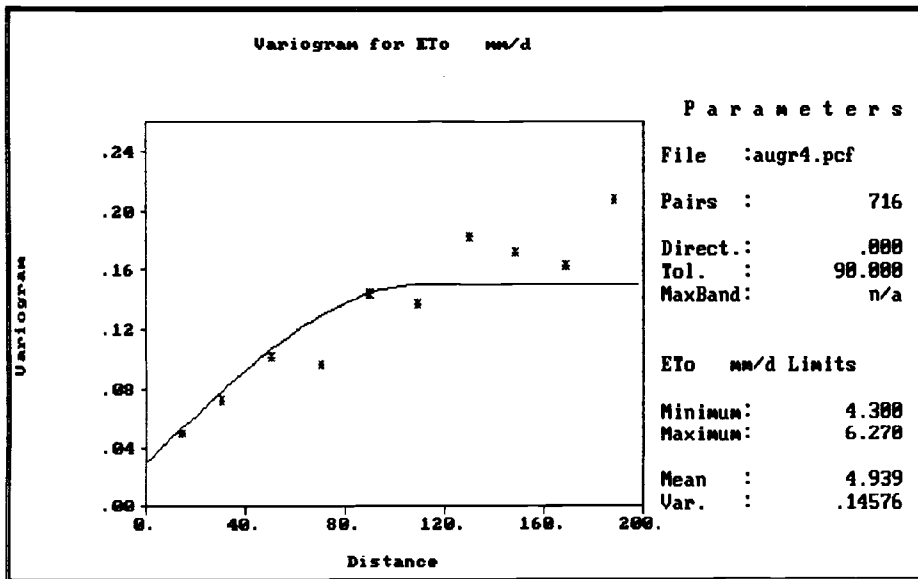
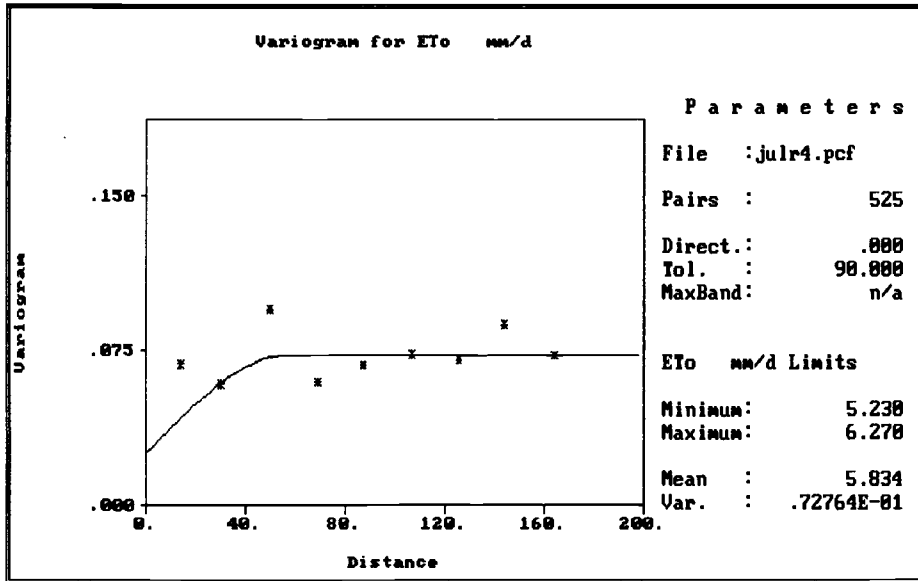


Figure 16: cont.

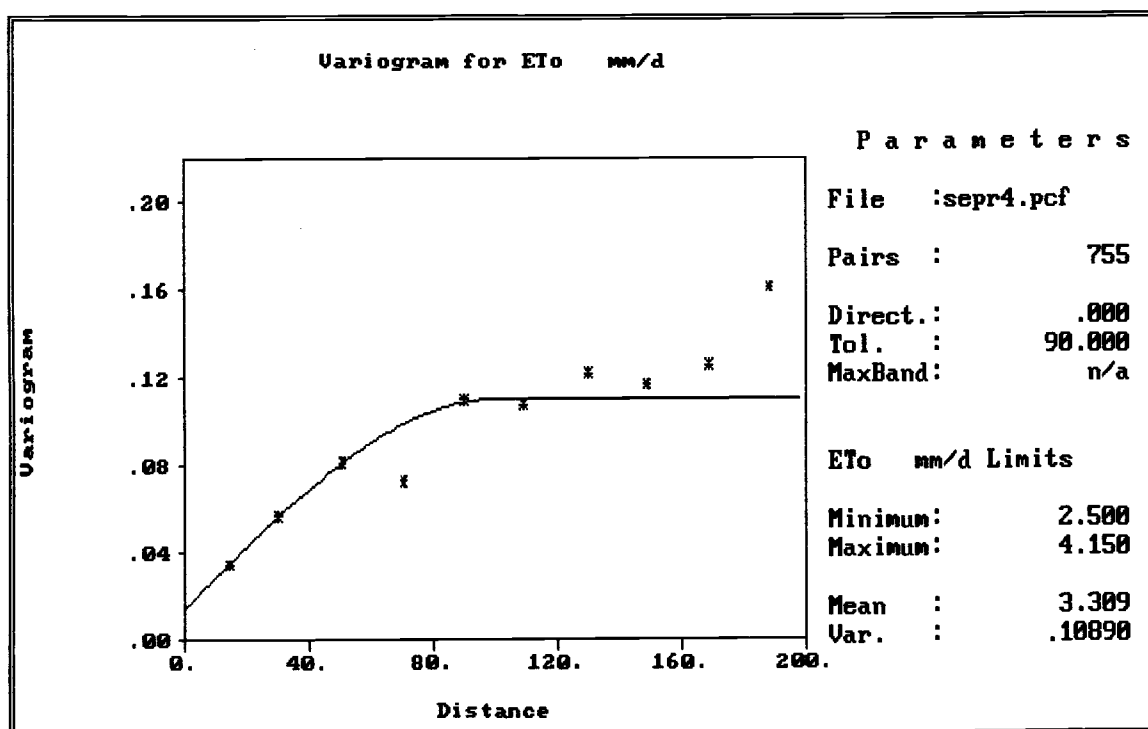


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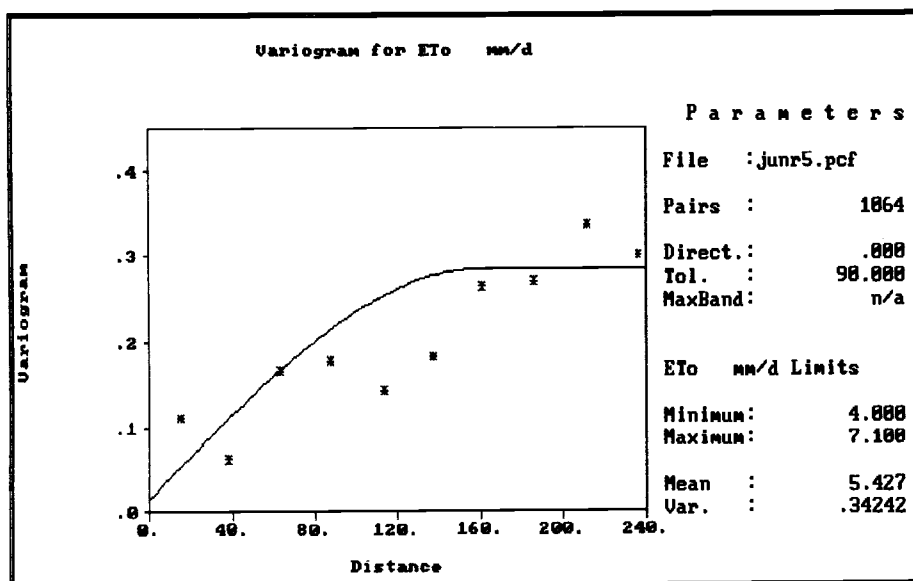
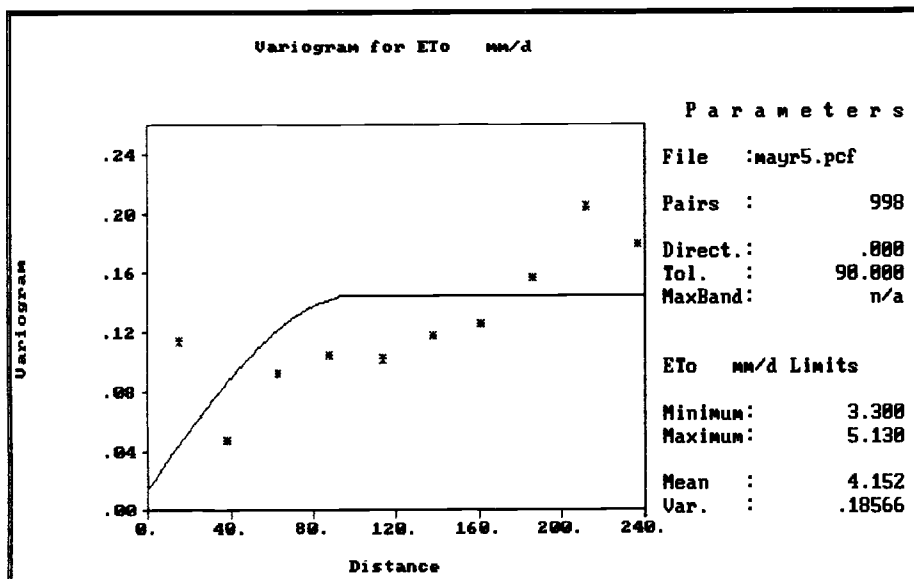


Figure 17: Variograms for Region 5

semi

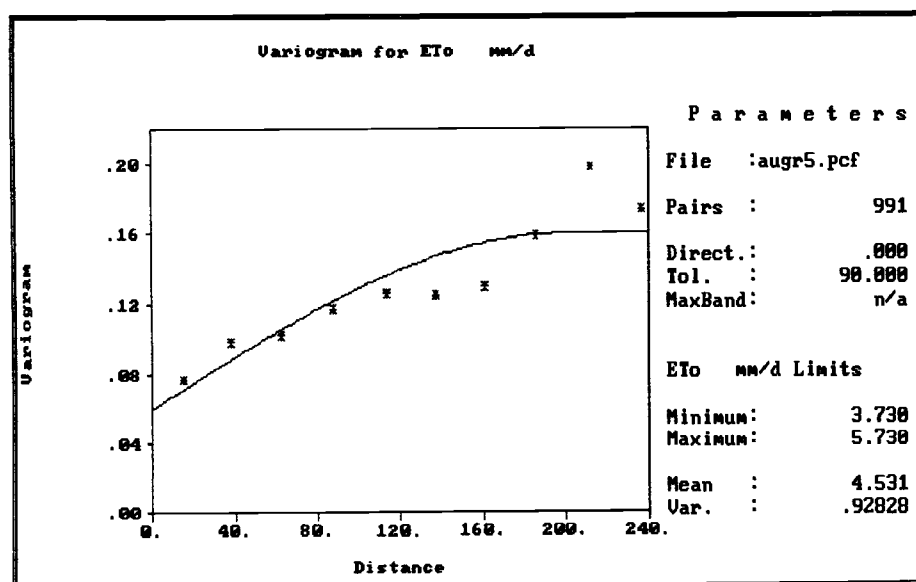
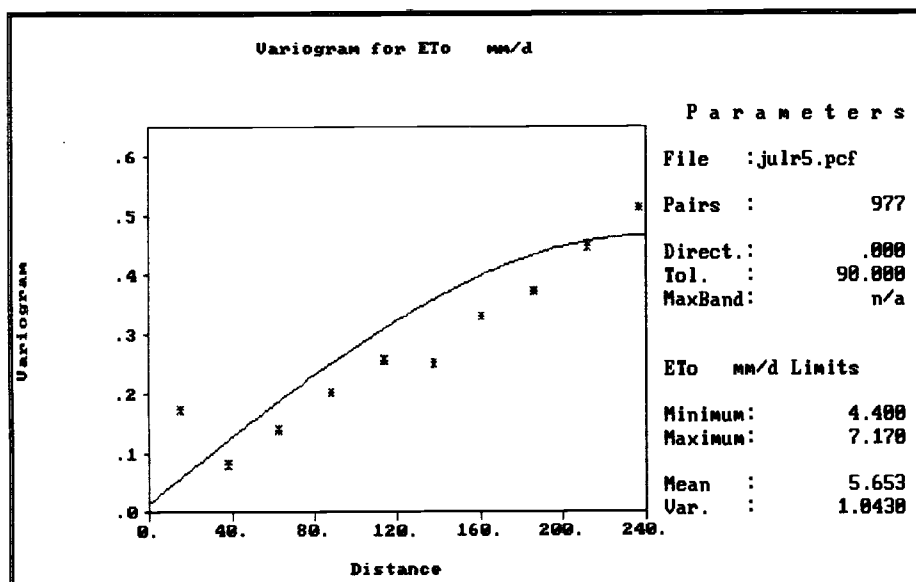


Figure 17: cont.

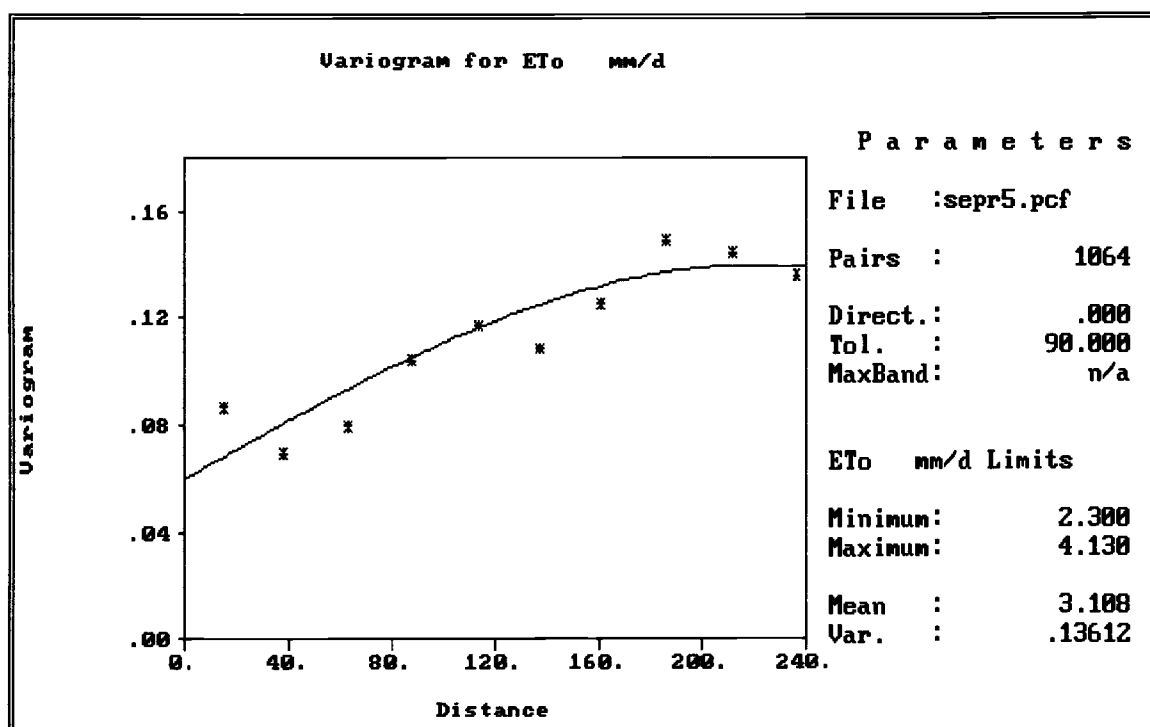


Figure 17: cont.



Table 5: Variogram and Cross Validation Results

	AKE	m <sub>se</sub>	S <sup>2</sup> <sub>se</sub>	Standard error	Deviation variable	VARIOGRAM:spherical model NUGGET	RANGE	SILL
REGION 1: COASTAL								
3YR AVERAGE DATA								
MAY	-0.019	-0.088	1.077	0.173	0.182	0.000	60.0	0.030
JUNE	0.008	0.026	1.128	0.217	0.227	0.000	85.0	0.052
JULY	0.008	0.027	1.030	0.239	0.251	0.000	70.0	0.063
AUGUST	0.004	0.008	1.072	0.262	0.266	0.000	70.0	0.071
SEPTEMBER	0.010	-0.047	1.002	0.145	0.156	0.000	65.0	0.024
REGION 2: WILLAMETTE VALLEY								
3YR AVERAGE DATA								
MAY	0.005	0.018	1.148	0.232	0.273	0.015	75.0	0.060
JUNE	0.010	0.042	1.186	0.208	0.213	0.015	65.0	0.030
JULY	0.000	-0.005	1.071	0.240	0.261	0.025	55.0	0.043
AUGUST	-0.002	-0.016	1.005	0.224	0.237	0.025	37.0	0.031
SEPTEMBER	0.006	0.022	1.000	0.169	0.180	0.015	38.0	0.017
REGION 3: SOUTHWESTERN								
3YR AVERAGE DATA								
MAY	0.089	0.098	0.999	0.413	0.569	0.000	86.0	0.327
JUNE	0.081	0.085	0.998	0.393	0.678	0.000	116.0	0.460
JULY	0.072	0.104	0.998	0.340	0.513	0.000	114.0	0.264
AUGUST	0.056	0.076	0.791	0.302	0.574	0.000	114.0	0.329
SEPTEMBER	0.047	0.101	1.000	0.230	0.341	0.000	107.0	0.116
REGION 4: NORTHEASTERN								
3YR AVERAGE DATA								
MAY	-0.021	-0.047	1.153	0.353	0.389	0.015	100.0	0.136
JUNE	-0.011	-0.027	1.147	0.346	0.377	0.035	110.0	0.107
JULY	-0.006	-0.031	1.045	0.270	0.270	0.025	57.0	0.048
AUGUST	-0.025	-0.049	1.086	0.338	0.382	0.030	110.0	0.120
SEPTEMBER	-0.008	-0.020	1.187	0.300	0.330	0.015	100.0	0.095
REGION 5: SOUTHEASTERN								
3YR AVERAGE DATA								
MAY	0.002	-0.003	1.170	0.297	0.431	0.015	100.0	0.130
JUNE	-0.009	-0.019	1.180	0.327	0.585	0.015	160.0	0.270
JULY	-0.008	-0.015	1.125	0.381	0.670	0.015	240.0	0.450
AUGUST	-0.013	-0.038	1.076	0.336	0.400	0.060	200.0	0.100
SEPTEMBER	-0.005	-0.019	0.993	0.298	0.369	0.060	220.0	0.080

#### 5.4 COMPARISON WITH YEARLY DATA

For geostatistics to be operational in estimating regional evapotranspiration, it is desirable to have one model variogram that would be representative of the spatial correlation between known weather stations giving local estimates of ETr for the region. This model could allow for real time analysis of regional ETr by removing the time consuming and complicated variogram analysis. To test this hypothesis, a model variogram for each month within the various regions was determined for the average ETr estimates. These model variograms were then used as the model variograms for the individual years (1985, 1986, and 1987). The cross validation procedure was performed to determine the validity of using these models.

Tables 6 through 9 give the results obtained from the cross validation test. The model variograms used for each month, year, and region satisfied the cross validation criteria over fifty percent of the time. However, there was no consistency to when the model variograms satisfied or failed the criteria. All the regions except for region 5 had at least one time that the model failed the criteria. Regions 1 and 3 exhibited the worst results from the cross validation analysis using the model variograms from the average ETr estimates.

Why some model variograms from average ETr estimates failed in the analysis of the individual years and others did not might be a consequence of climatic factors rather than geostatistics. The average ETr estimates were taken for only the three individual years. By developing the model variogram from long term average ETr estimates, the model might represent the region more accurately and provide better results when applied to individual years.

Table 6: Cross Validation Results for Region 1, Yearly Data

		AKE	$\bar{e}_{se}$	$S^2_{se}$	Standard error	Deviation variable	VARIOGRAM:spherical model NUGGET	RANGE	SILL
1985	MAY	-0.024	-0.112	1.046	0.164	0.187	0.000	60.0	0.030
	JUNE	-0.001	-0.005	1.040	0.195	0.214	0.000	85.0	0.052
	JULY	-0.019	0.059	1.273	0.301	0.322	0.000	70.0	0.063
	AUGUST	-0.006	-0.021	0.982	0.236	0.221	0.000	70.0	0.071
	SEPT	-0.019	-0.091	1.804	0.244	0.197	0.000	60.0	0.024
1986	MAY	-0.010	-0.048	1.425	0.227	0.209	0.000	60.0	0.030
	JUNE	0.015	0.053	1.272	0.247	0.252	0.000	85.0	0.052
	JULY	-0.001	-0.005	0.977	0.213	0.215	0.000	70.0	0.063
	AUGUST	0.013	-0.038	1.202	0.300	0.333	0.000	70.0	0.071
	SEPT	0.021	-0.105	1.961	0.266	0.214	0.000	60.0	0.024
1987	MAY	-0.019	-0.099	1.787	0.291	0.236	0.000	60.0	0.030
	JUNE	0.007	0.025	1.046	0.213	0.197	0.000	85.0	0.052
	JULY	0.000	0.006	0.931	0.223	0.226	0.000	70.0	0.063
	AUGUST	-0.001	0.001	1.261	0.304	0.289	0.000	70.0	0.071
	SEPT	0.000	0.002	1.303	0.190	0.187	0.000	60.0	0.024

Table 7: Cross Validation Results for Region 2, Yearly Data

		AKE	$\bar{e}_{se}$	$S^2_{se}$	Standard error	Deviation variable	VARIOGRAM:spherical model NUGGET	RANGE	SILL
1985	MAY	0.005	0.019	1.169	0.238	0.291	0.015	75.0	0.060
	JUNE	0.003	0.013	1.258	0.224	0.221	0.015	65.0	0.030
	JULY	-0.002	-0.014	1.087	0.243	0.260	0.025	55.0	0.043
	AUGUST	-0.002	-0.011	1.029	0.233	0.239	0.025	37.0	0.031
	SEPT	0.004	0.020	1.025	0.159	0.173	0.015	38.0	0.010
1986	MAY	0.002	0.010	1.114	0.230	0.253	0.015	75.0	0.060
	JUNE	0.010	0.040	1.060	0.184	0.199	0.015	65.0	0.030
	JULY	0.000	-0.003	1.077	0.246	0.274	0.025	55.0	0.043
	AUGUST	-0.004	-0.023	0.935	0.210	0.225	0.025	37.0	0.031
	SEPT	0.005	0.024	0.925	0.147	0.167	0.015	38.0	0.010
1987	MAY	0.006	0.021	1.221	0.246	0.280	0.015	75.0	0.060
	JUNE	0.016	0.068	1.366	0.241	0.236	0.015	65.0	0.030
	JULY	0.000	-0.005	1.169	0.262	0.269	0.025	55.0	0.043
	AUGUST	0.003	0.002	1.155	0.257	0.269	0.025	37.0	0.031
	SEPT	0.001	0.003	1.163	0.182	0.194	0.015	38.0	0.010

Table 8: Cross Validation Results for Region 3, Yearly Data

		AKE	Mse	S <sup>2</sup> <sub>se</sub>	Standard error	Deviation variable	VARIOGRAM:spherical model NUGGET	RANGE	SILL
1985	MAY	0.095	0.100	1.097	0.475	0.574	0.000	86.0	0.327
	JUNE	0.086	0.087	0.956	0.425	0.676	0.000	116.0	0.460
	JULY	0.059	0.083	0.971	0.345	0.493	0.000	114.0	0.264
	AUGUST	0.072	0.094	0.873	0.355	0.507	0.000	114.0	0.329
	SEPT	0.058	0.123	1.418	0.359	0.385	0.000	107.0	0.116
1986	MAY	0.090	0.094	1.007	0.424	0.572	0.000	86.0	0.327
	JUNE	0.073	0.077	0.977	0.363	0.670	0.000	116.0	0.460
	JULY	0.075	0.108	0.987	0.343	0.573	0.000	114.0	0.264
	AUGUST	0.049	0.068	0.730	0.271	0.572	0.000	114.0	0.329
	SEPT	0.057	0.117	1.087	0.263	0.369	0.000	107.0	0.116
1987	MAY	0.079	0.088	0.937	0.368	0.577	0.000	86.0	0.327
	JUNE	0.084	0.088	1.172	0.436	0.686	0.000	116.0	0.460
	JULY	0.071	0.098	1.014	0.359	0.523	0.000	114.0	0.264
	AUGUST	0.053	0.075	0.849	0.306	0.567	0.000	114.0	0.329
	SEPT	0.019	0.054	1.193	0.229	0.288	0.000	107.0	0.116

Table 9: Cross Validation Results for Region 4, Yearly Data

		AKE	Mse	S <sup>2</sup> <sub>se</sub>	Standard error	Deviation variable	VARIOGRAM:spherical model NUGGET	RANGE	SILL
1985	MAY	-0.023	-0.045	1.236	0.392	0.397	0.015	100.0	0.136
	JUNE	-0.034	-0.077	1.346	0.433	0.520	0.035	110.0	0.107
	JULY	-0.007	-0.026	1.272	0.330	0.330	0.025	57.0	0.048
	AUGUST	-0.028	-0.058	1.153	0.349	0.325	0.030	110.0	0.120
	SEPT	-0.020	-0.050	1.099	0.278	0.317	0.015	100.0	0.095
1986	MAY	-0.019	-0.038	1.027	0.305	0.349	0.015	100.0	0.136
	JUNE	-0.011	-0.025	1.018	0.313	0.354	0.035	110.0	0.107
	JULY	-0.012	-0.039	1.163	0.308	0.280	0.025	57.0	0.048
	AUGUST	-0.010	-0.017	1.049	0.312	0.323	0.030	110.0	0.120
	SEPT	-0.017	-0.042	0.977	0.256	0.276	0.015	100.0	0.095
1987	MAY	-0.029	-0.067	1.072	0.349	0.393	0.015	100.0	0.136
	JUNE	-0.034	-0.081	1.197	0.397	0.501	0.035	110.0	0.107
	JULY	-0.004	-0.019	1.073	0.281	0.286	0.025	57.0	0.048
	AUGUST	-0.024	-0.054	1.058	0.339	0.464	0.030	110.0	0.120
	SEPT	-0.007	-0.022	0.923	0.234	0.267	0.015	100.0	0.095

Table 10: Cross Validation Results for Region 5, Yearly Data

		AKE	m <sub>se</sub>	S <sup>2</sup> <sub>se</sub>	Standard error	Deviation variable	VARIOGRAM:spherical model NUGGET	RANGE	SILL
1985	MAY	0.005	0.005	1.323	0.351	0.544	0.015	100.0	0.130
	JUNE	-0.001	-0.010	1.391	0.391	0.621	0.015	160.0	0.270
	JULY	-0.003	-0.009	1.153	0.348	0.608	0.015	240.0	0.450
	AUGUST	-0.010	-0.035	1.037	0.327	0.402	0.060	200.0	0.100
	SEPT	-0.002	-0.012	0.913	0.275	0.336	0.060	220.0	0.080
1986	MAY	0.009	0.017	0.869	0.254	0.445	0.015	100.0	0.130
	JUNE	-0.004	-0.009	1.132	0.327	0.643	0.015	160.0	0.270
	JULY	0.002	0.002	1.355	0.366	0.647	0.015	240.0	0.450
	AUGUST	-0.011	-0.034	1.078	0.336	0.435	0.060	200.0	0.100
	SEPT	-0.003	-0.009	0.754	0.226	0.353	0.060	220.0	0.080
1987	MAY	-0.003	-0.014	1.253	0.336	0.518	0.015	100.0	0.130
	JUNE	-0.001	-0.003	1.046	0.306	0.555	0.015	160.0	0.270
	JULY	-0.008	-0.010	1.019	0.309	0.631	0.015	240.0	0.450
	AUGUST	-0.012	-0.041	1.029	0.328	0.416	0.060	200.0	0.100
	SEPT	-0.005	-0.019	1.025	0.313	0.362	0.060	220.0	0.080

## 5.5 CONTOUR MAPS OF KRIGED ETr AND STANDARD DEVIATIONS FOR REGIONS

The averaged ETr estimates during July and September for regions 1, 2, 4, and 5 were used in the kriging analysis. Kriging was performed to estimate reference evapotranspiration over a grid superimposed on the region. The grid size was on a 10 km by 10 km interval. Using the model variogram validated for those months and regions along with the observed ETr estimates, the KRIGE routine in Geo-EAS estimated ETr and the standard deviation at the unknown grid points applying the kriging analysis discussed in the Literature Review. SURFER was used to produce the contour maps for the regions during July and September. Figures 18 through 33 are contour maps of kriged ETr estimates and the error associated with the kriged estimates plotted from the SURFER software package.

In general, the maps within each region displayed a consistent shape of contours for ETr and the standard deviation of the kriging error between July and September. As expected, the contour maps show a higher rate of ETr for the middle of the growing season (July) compared to the end of the season (September). This trend agreed with that seen in Fig. 8. The contour interval was set at the minimum standard deviation of the error for the region. In practice, the contour interval is usually two times the standard deviation. However, if this contour interval

had been applied, only one contour would be plotted for most regions and not enough information about the shape of the contour would be given. This result strongly suggests that the regions used in the analysis are homogeneous. A problem occurred in region 1 due to the extreme ratio of length to width. To show contour lines for this region, the X and Y scale were manipulated so that one X unit was equal to two Y units.

It was noticed that the values of ETr of individual meteorological stations within the regions influenced the shape of the contour lines and the shape did not necessarily correspond to topographic effects in Oregon. In region 1, the contour lines did not follow a north to south orientation as expected from the topographic and vegetation influence of the Coastal range. One explanation is that the weather stations used for the ETr estimates are generally representative of the valleys in each region. For use in hydrologic modeling or irrigation system design and scheduling in regional valleys, the kriged ETr estimates could be very satisfactory. However, for use in large scale hydrologic modeling or global circulation models, a method to account for the topographic and vegetation effects must be included in the kriged ETr estimates.

Comparing contours between regions was difficult because the contour lines were not always able to be set to the same contour interval. To effectively utilize these contour maps within regions for the whole state, there must be some method to deal with the transition zones between regions. A possibility is to combine kriged estimates from each region into one file representing the whole state and produce contour plots from the overall data file.

The contour maps for standard deviations of the kriged estimates show the distribution of the errors over the region. The standard deviation was generally uniform over a region. Typically, there was a low standard deviation for a homogeneous region with a high number of sample locations (weather stations). Since the individual regions were already assumed homogeneous (stationarity), the standard deviations depended mainly on the station density. Therefore, the interest in these contour maps of standard deviations is in identifying locations

where additional weather stations could be placed thereby reducing the error of the estimate and improving the ETr estimates. Looking at region 5, the lower right corner of the region had the highest standard deviations which suggests a lack of stations to represent that area.

## CONTOUR MAPS OF ETr

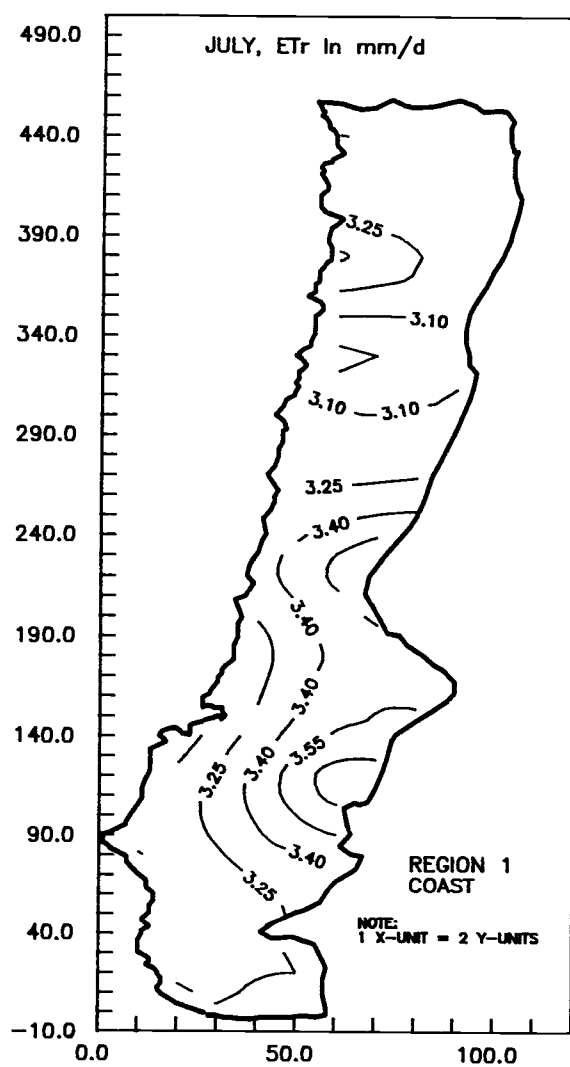


Figure 18: Contour Map of Kriged ETr estimates for July in Region 1



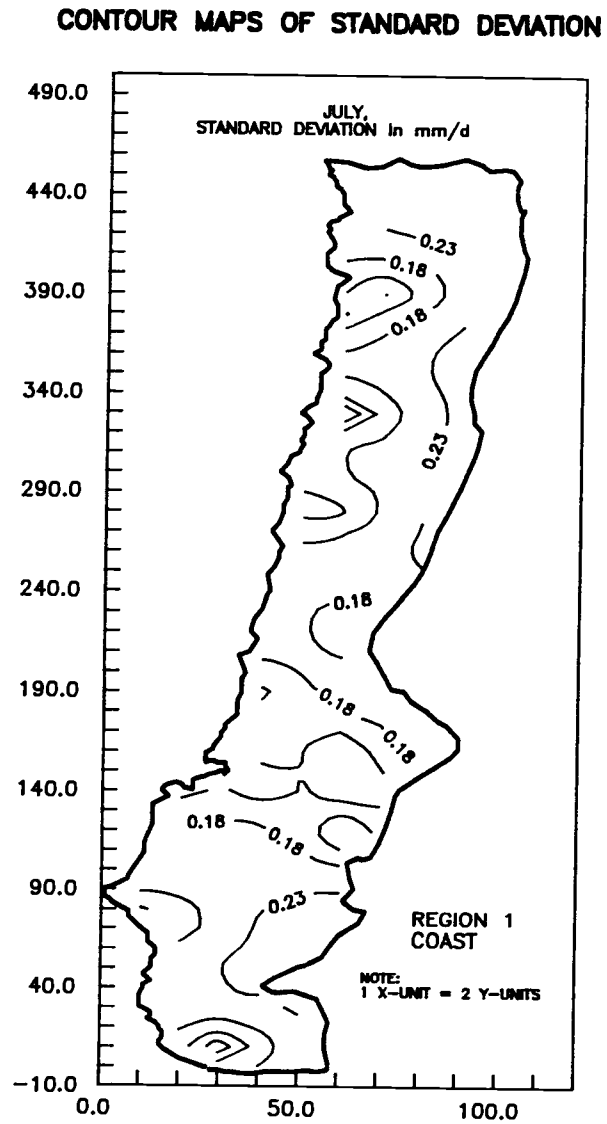


Figure 19: Contour Map of Kriged Standard Deviations for July in Region 1

## CONTOUR MAPS OF ETr

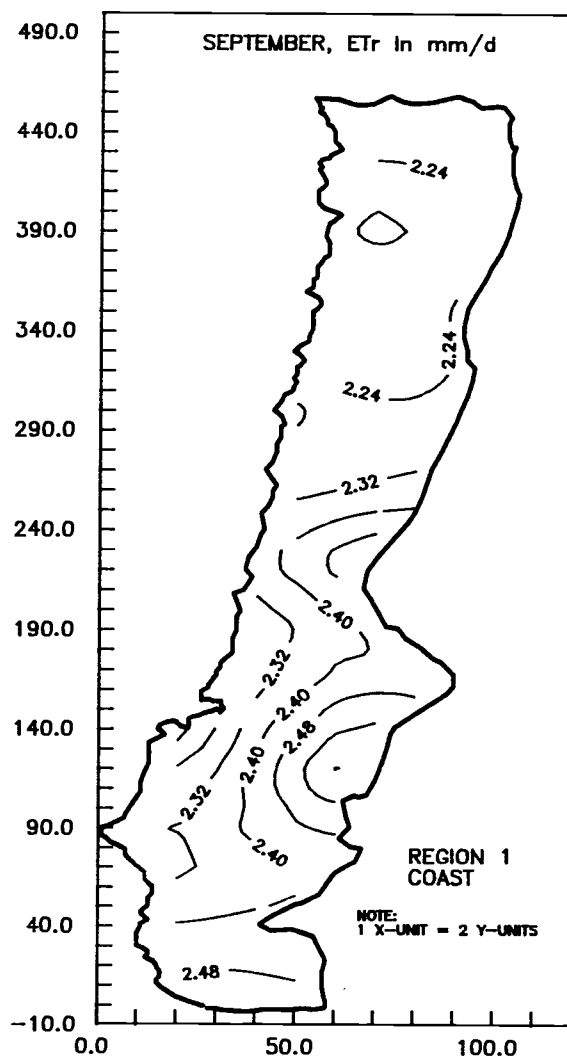


Figure 20: Contour Map of Kriged ETr estimates for Sept. in Region 1

### CONTOUR MAPS OF STANDARD DEVIATION

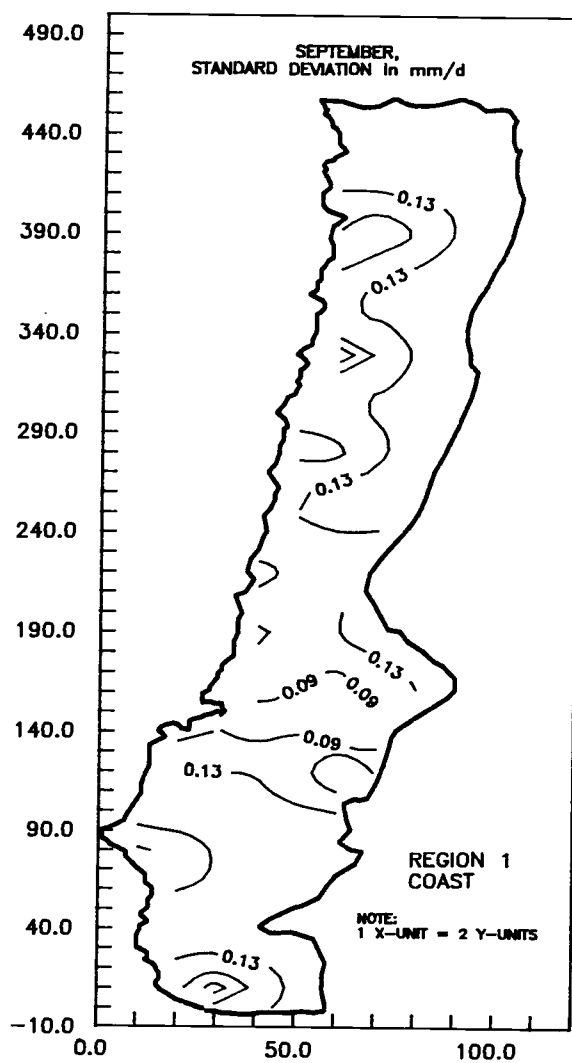


Figure 21: Contour Map of Kriged Standard Deviations for Sept. in Region 1

## CONTOUR MAPS OF ETr

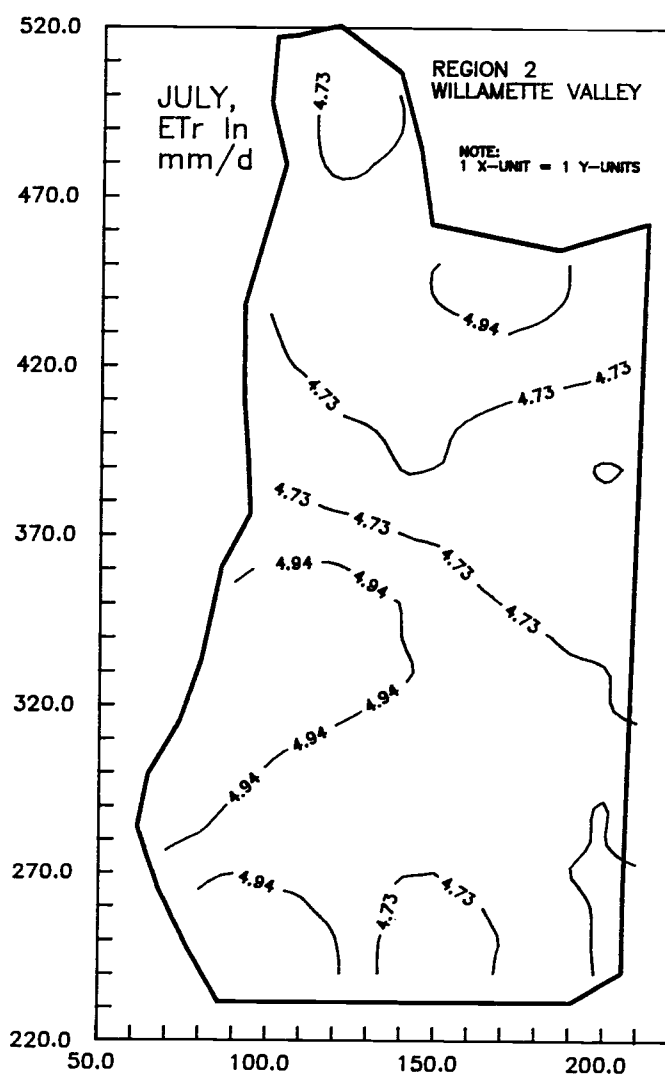


Figure 22: Contour Map of Kriged ETr estimates for July in Region 2

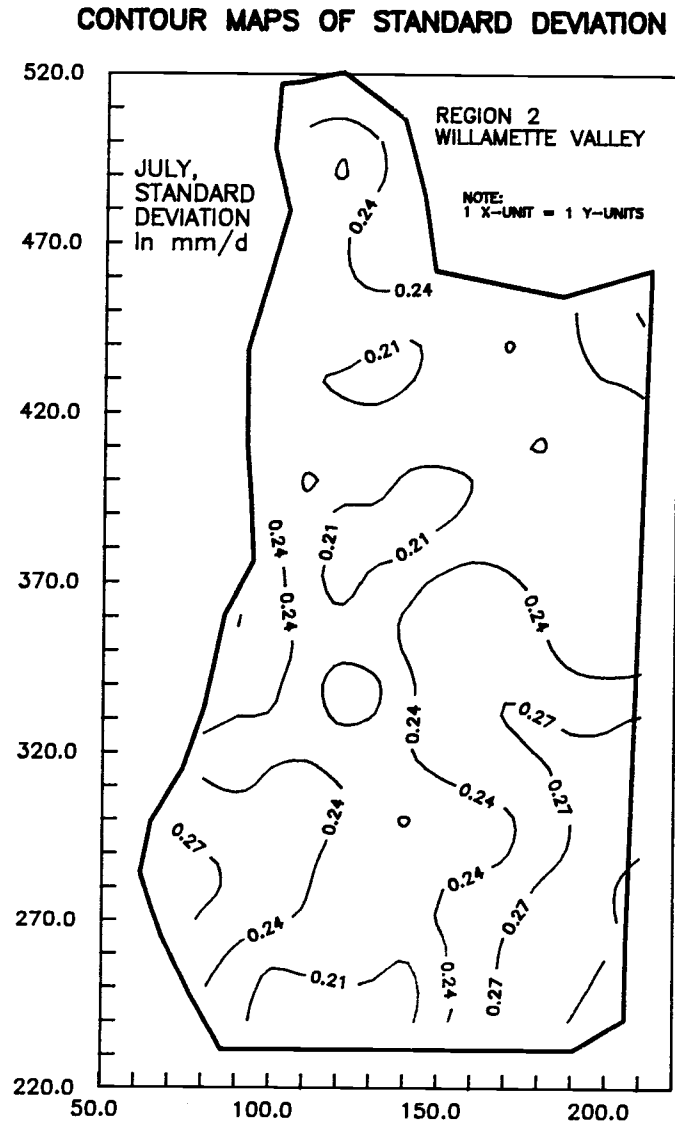


Figure 23: Contour Map of Kriged Standard Deviations for July in Region 2



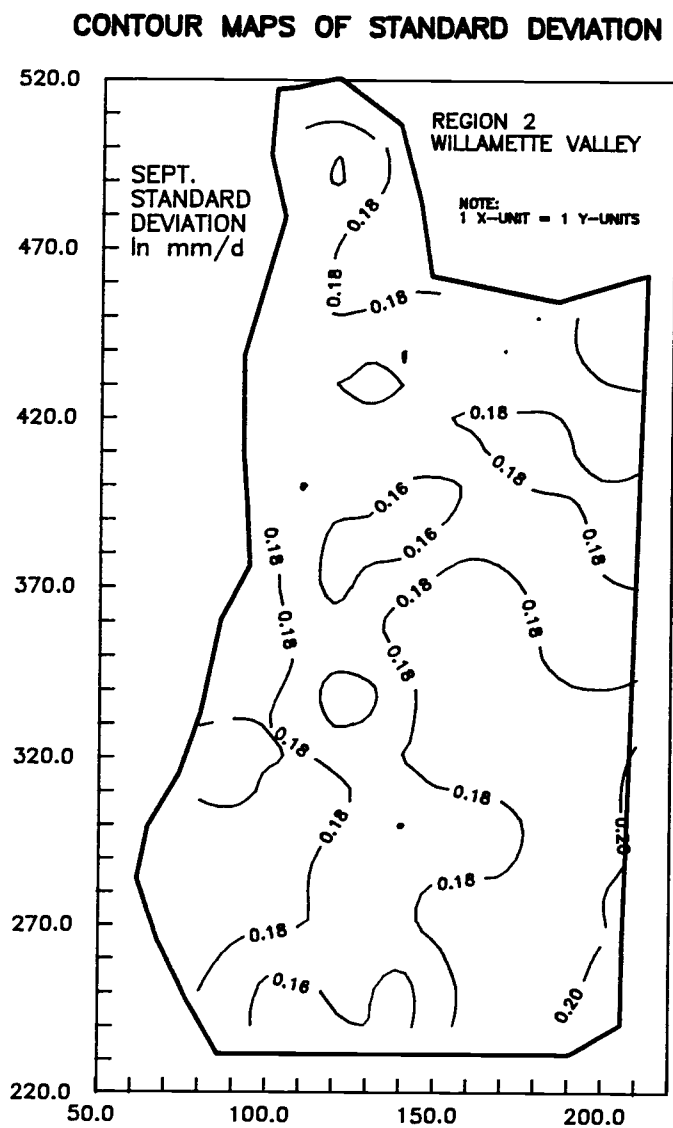


Figure 25: Contour Map of Kriged Standard Deviations for Sept. in Region 2

## CONTOUR MAPS OF ETr

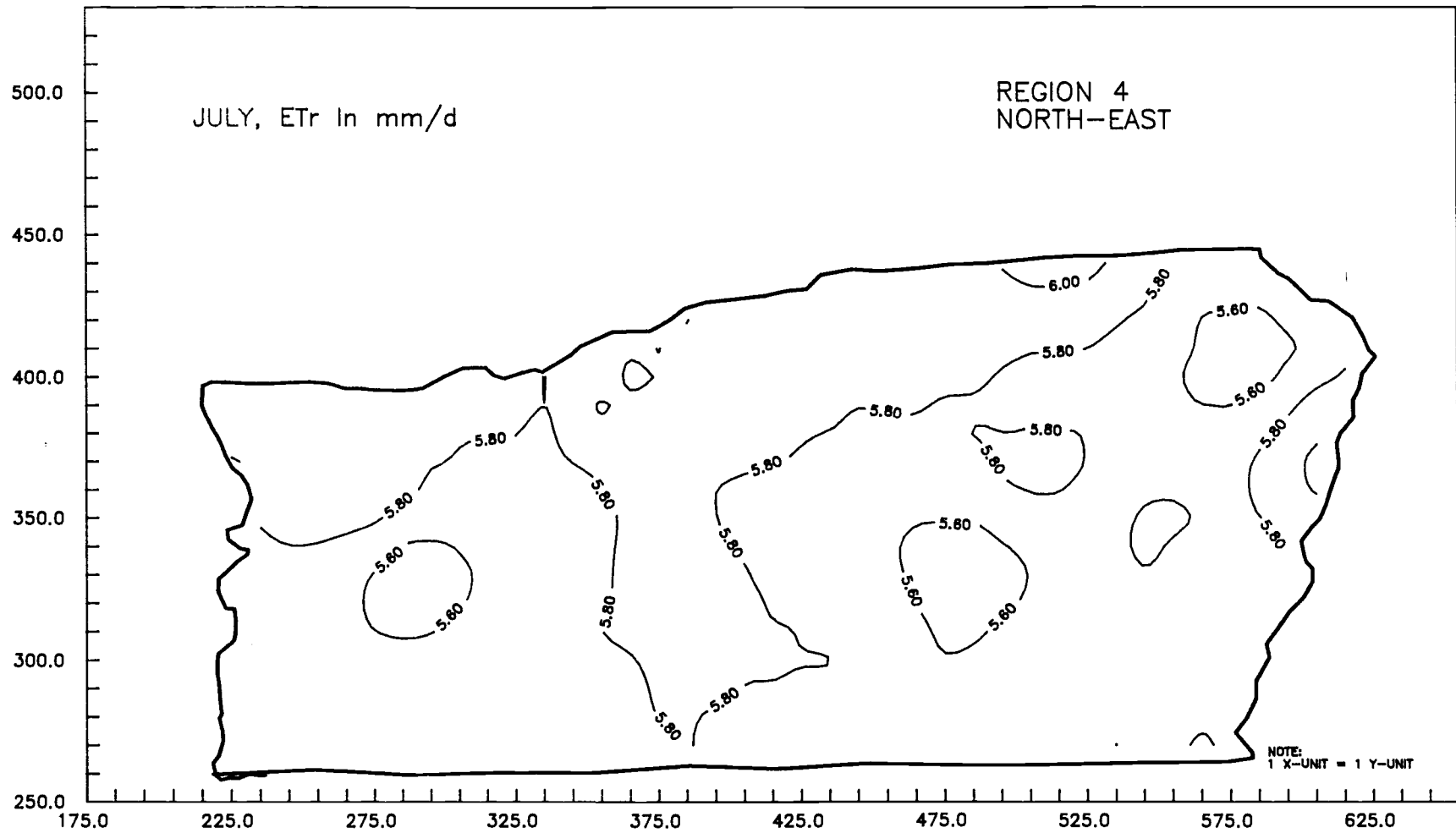


Figure 26: Contour Map of Kriged ETr estimates for July in Region 4



## CONTOUR MAPS OF STANDARD DEVIATION

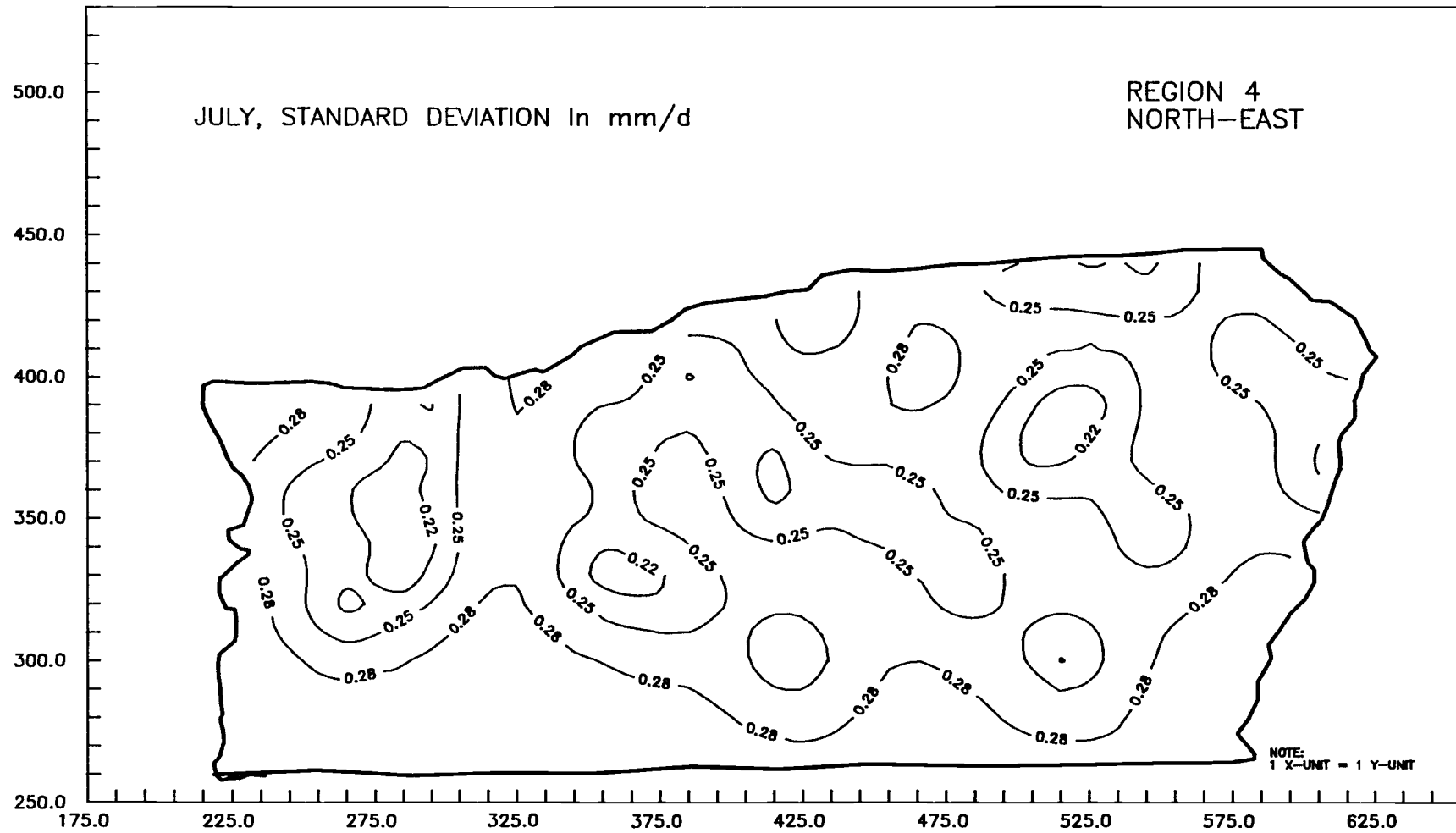


Figure 27: Contour Map of Kriged Standard Deviations for July in Region 4

## CONTOUR MAPS OF ETr

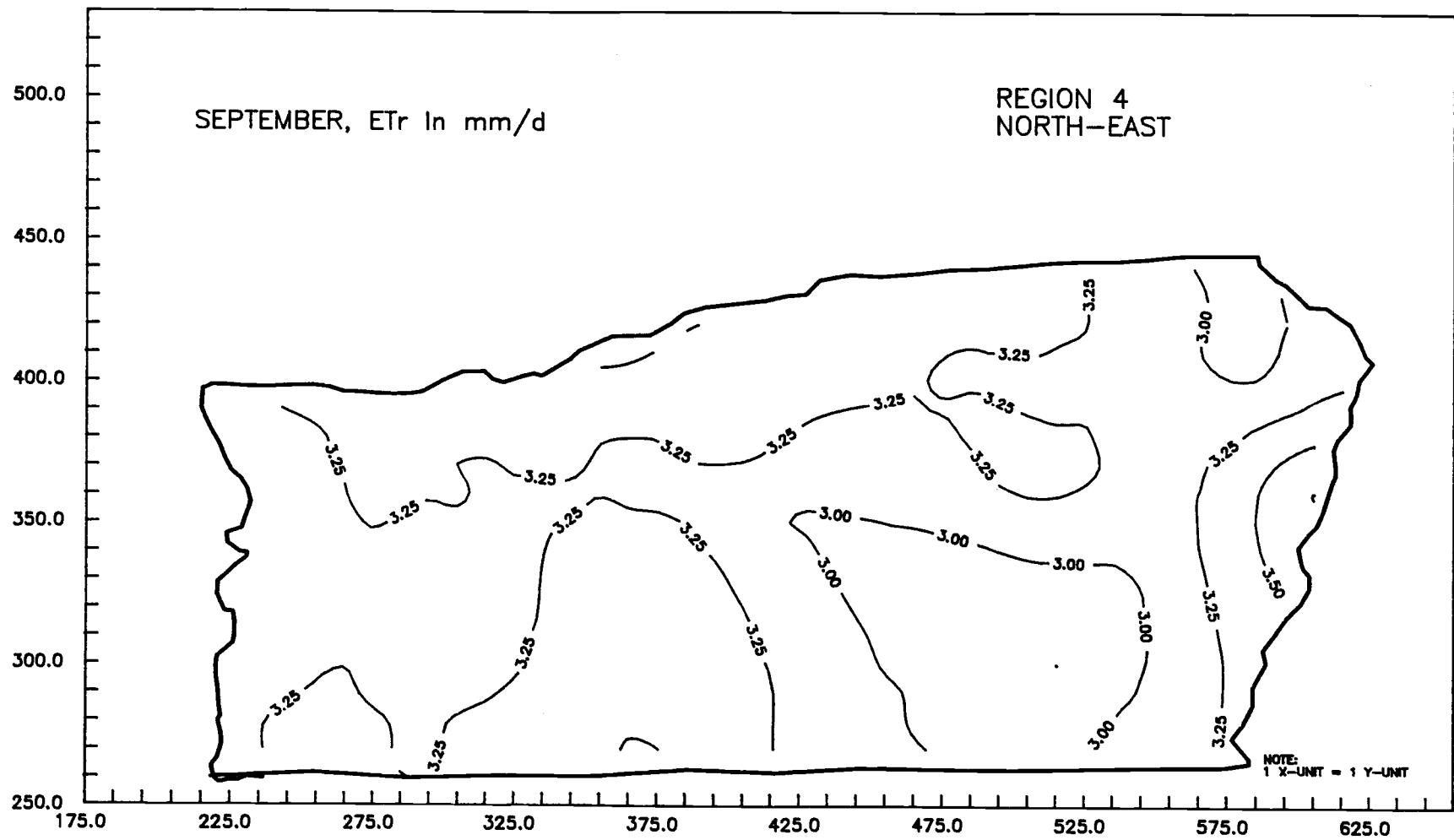


Figure 28: Contour Map of Kriged ETr estimates for Sept. in Region 4

## CONTOUR MAPS OF STANDARD DEVIATION

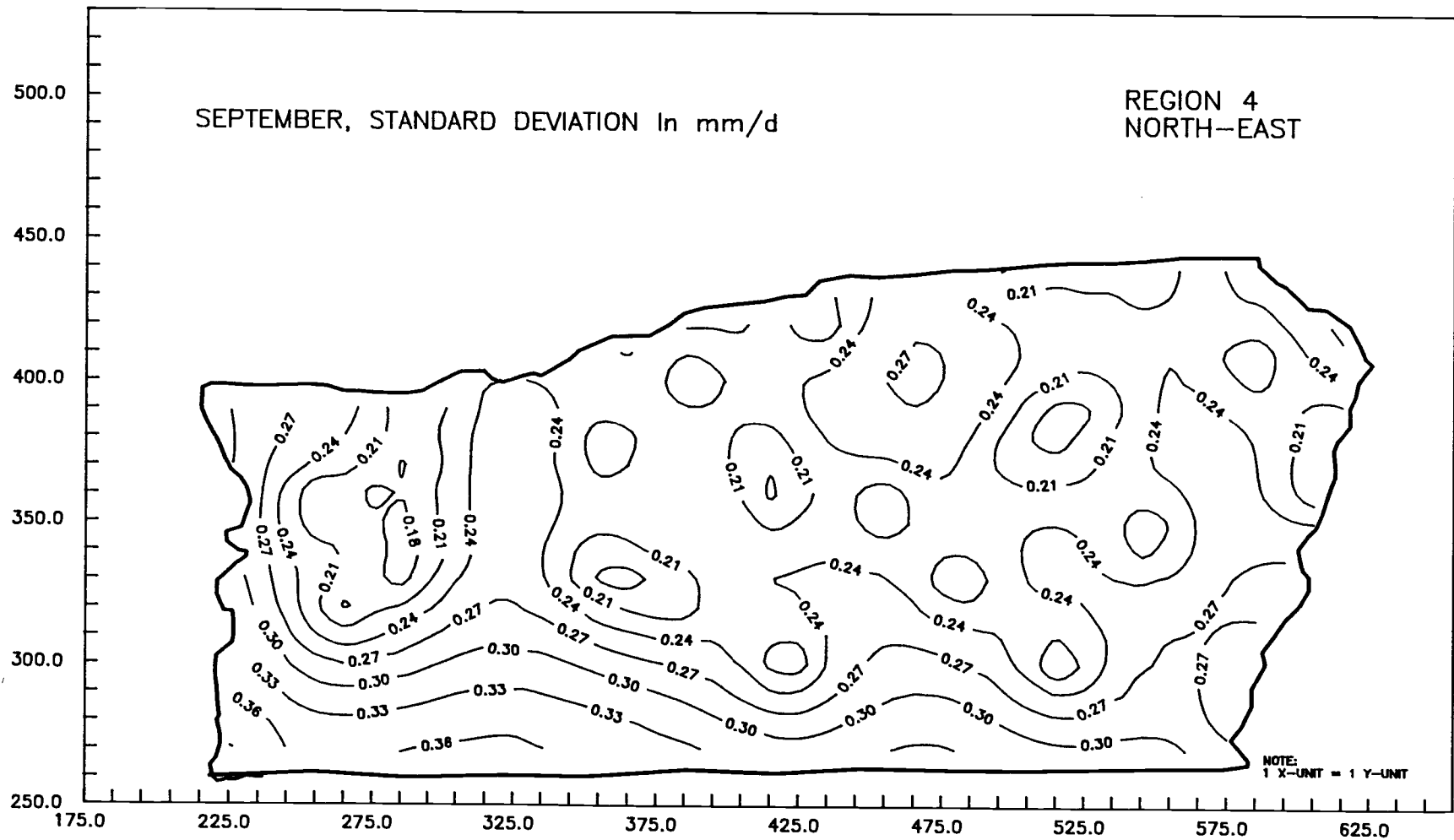


Figure 29: Contour Map of Kriged Standard Deviations for Sept. in Region 4

# CONTOUR MAPS OF ETr

JULY, ETr In mm/d

REGION 5  
SOUTH-EAST

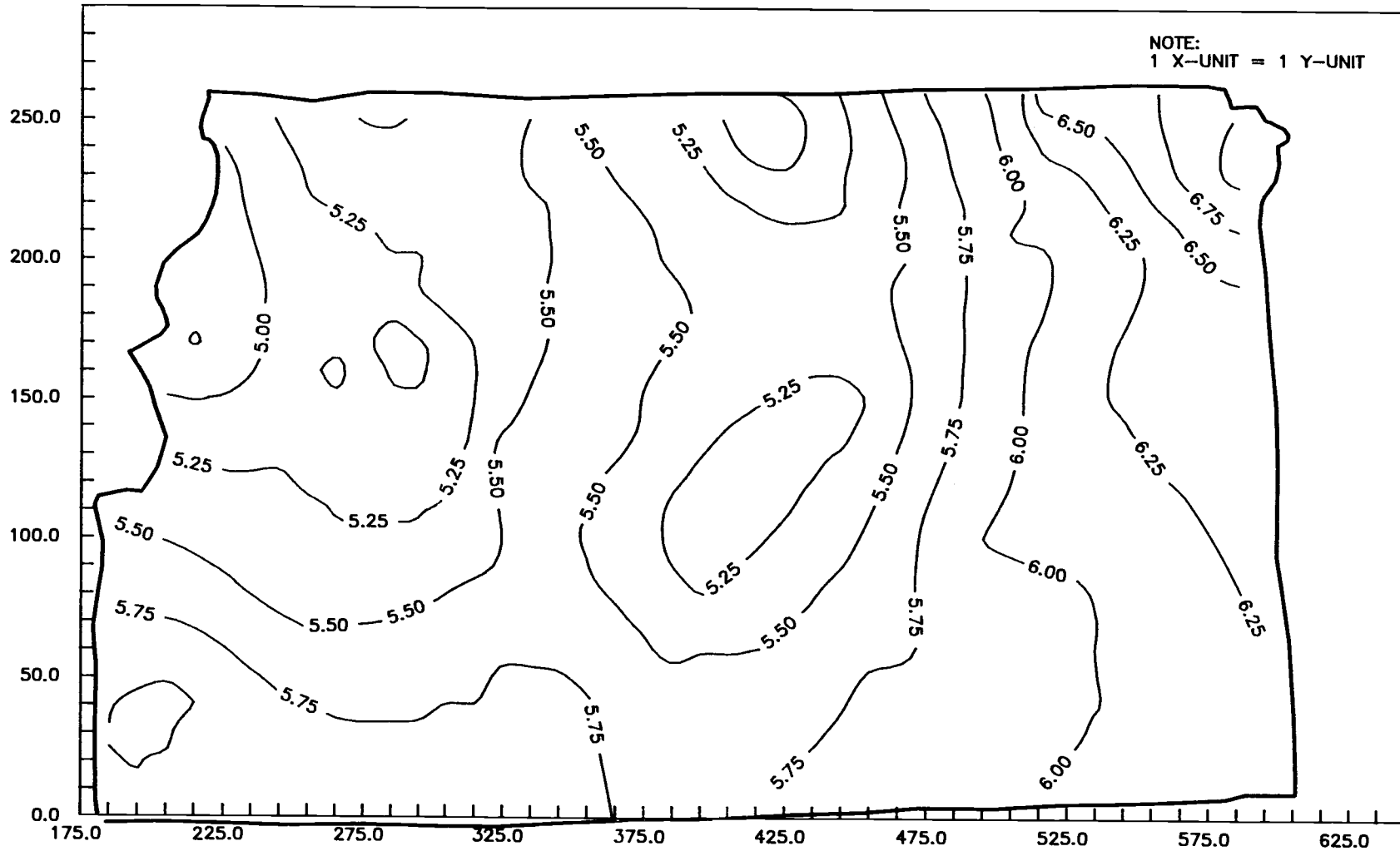


Figure 30: Contour Map of Kriged ETr estimates for July in Region 5

# CONTOUR MAPS OF STANDARD DEVIATION

JULY, STANDARD DEVIATION In mm/d

REGION 5  
SOUTH-EAST

NOTE:  
1 X-UNIT = 1 Y-UNIT

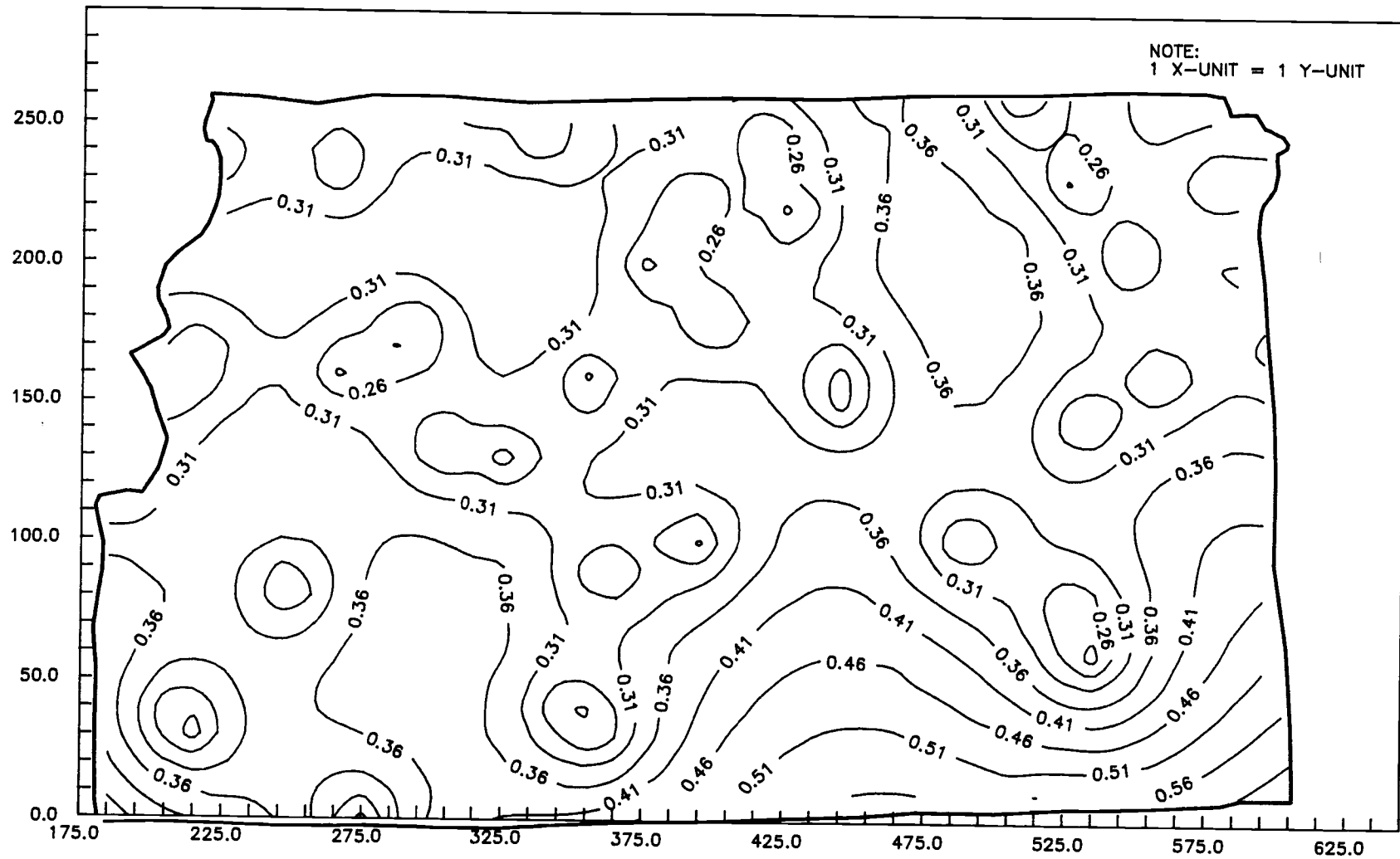


Figure 31: Contour Map of Kriged Standard Deviations for July in Region 5

# CONTOUR MAPS OF ETr

SEPTEMBER, ETr In mm/d

REGION 5  
SOUTH-EAST

NOTE:  
1 X-UNIT = 1 Y-UNIT

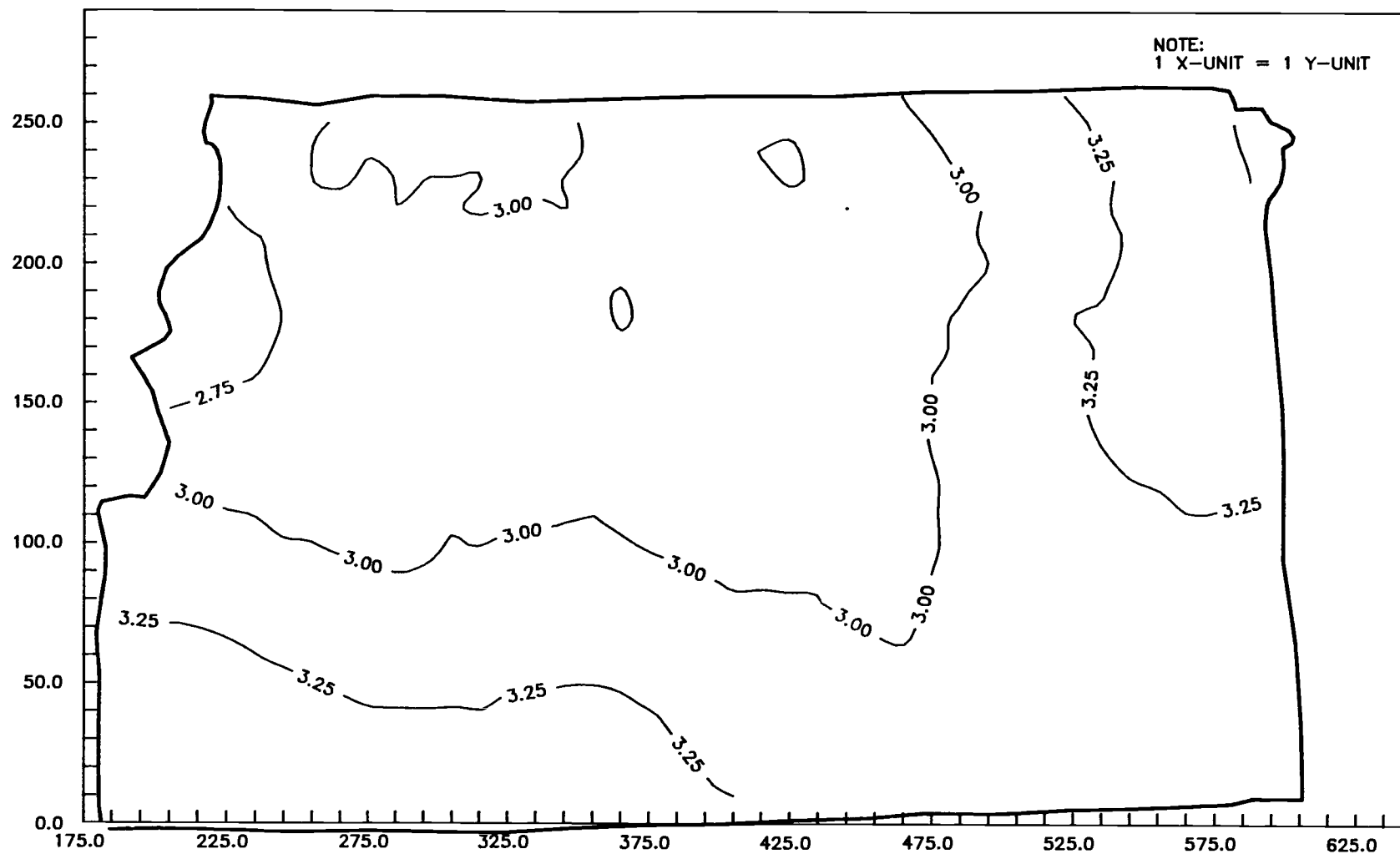


Figure 32: Contour Map of Kriged ETr estimates for Sept. in Region 5

## CONTOUR MAPS OF STANDARD DEVIATION

SEPTEMBER, STANDARD DEVIATION In mm/d

REGION 5  
SOUTH-EAST

NOTE:  
1 X-UNIT = 1 Y-UNIT

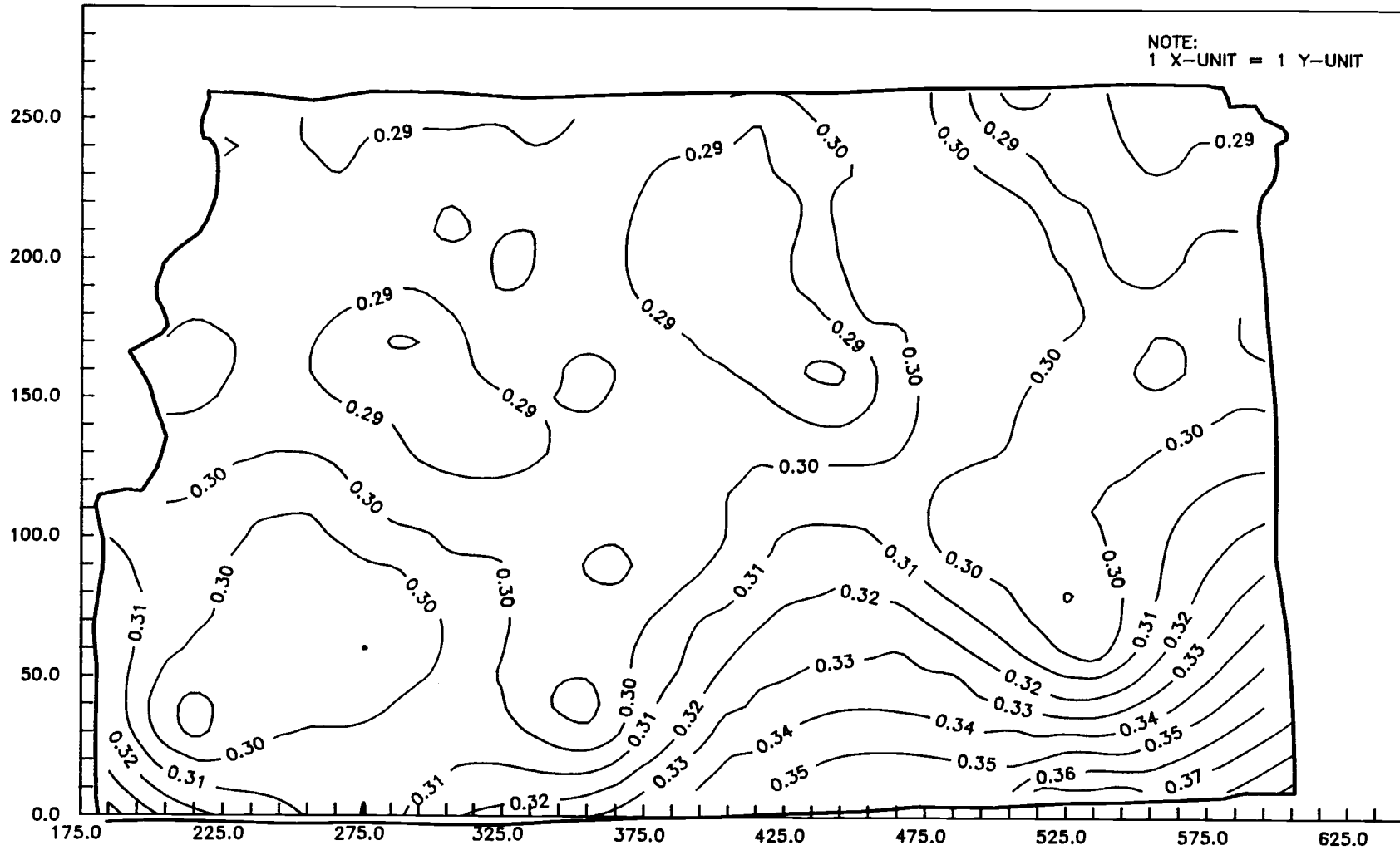


Figure 33: Contour Map of Kriged Standard Deviations for Sept. in Region 5

## 6 CONCLUSIONS AND RECOMMENDATIONS

The FAO-modified Blaney-Criddle method was used to compute local estimates of monthly reference evapotranspiration, ETr, for 180 weather stations over the state of Oregon during 1985, 1986, and 1987. This method was selected over other local estimating methods because previous research in states adjacent to Oregon indicated this to be the most accurate temperature-based method. In addition, since this method relies predominantly on temperature, it was found to be compatible with the weather data available throughout Oregon.

The state was divided into five climatic regions based on topographic features and local meteorological conditions: 1) Coast, 2) Willamette Valley, 3) Southwestern Valley, 4) North East, and 5) South East. The ETr estimates were allocated to their respective regions and averaged over the three years. The average ETr estimates were used to compute sample variograms for each month from May through September in each region. Model variograms were fitted to the sample variograms using the spherical model and validated through a cross validation procedure. For four out of the five regions, a verified spherical model was obtained for the individual months. It was difficult to confirm that the model variograms for region 3 were valid because the values for AKE and the mean standardized error ( $m_{se}$ ) diverged more from zero when compared to the other regions. The small number of ETr estimates in this region contributed to the fact that model variograms were not able to be verified.

Amegee (1985) commented on the problem of using all data available on a large heterogeneous region to compute the sample variograms compared to computing the sample variograms for separate climatic regions within the larger geographic region. The strength of subregional analysis is that the stationarity assumptions are better sustained. However, the limited number of samples available within the region makes it more difficult to successfully fit a model variogram to the data. This was particularly the case in region 3. The state of Oregon was divided into 5 climatic regions. A closer look at the data in each region might provide



justification for combining certain regions together. Regions might be able to be combined resulting in more ETr estimates to characterize spatial variation without jeopardizing the stationary assumptions required for geostatistics.

The model variograms determined for the average ETr estimates were used as the variograms for the individual years (1985, 1986, and 1987) to test the hypothesis that one model variogram could represent the spatial correlation of ETr for the region. From the cross validation results, no valid conclusions to support this hypothesis could be made due to the inconsistency seen in the success and failure rate of applying the model variograms for the average ETr data to the individual years. It is recommended to develop the model variograms from long term average ETr estimates which could provide better results when applied to individual years.

Kriging was performed on the average ETr estimates for July and September in regions 1, 2, 4, and 5. Using the validated model variograms for these months and regions along with the observed ETr estimates, the kriging analysis was used to estimate the ETr and standard deviation of the error over a grid representing the region. The grid interval was 10 km by 10 km. In general, the maps within each region displayed a consistent shape of contours for ETr and the standard deviation of the kriging error between the months. The contours of standard deviation of the kriging error also agreed with the weather station densities within the regions and were generally uniform over a region. The knowledge of the standard deviation of the kriging errors could assist in identifying locations where additional weather stations could be placed thereby reducing the error of the estimate and improving the ETr estimates.

In practice, the contour interval is often two times the standard deviation. However, in this project, the contour interval was set at the minimum standard deviation of the error for the region. This contour interval had to be applied because only one contour could be plotted for most regions if the interval was set at twice the standard deviation. This fact strongly suggests that the regions used in the analysis are homogeneous.

It was noticed that the values of ETr of individual meteorological stations within the regions influenced the shape of the contour lines and the shape did not necessarily correspond to topographic effects in Oregon. This was particularly seen in region 1 where the contour lines did not follow a north to south orientation as expected. One explanation is that the weather stations used for the ETr estimates are generally representative of the valleys in each region. For use in hydrologic modeling or irrigation system design and scheduling in regional valleys, the kriged ETr estimates could be very satisfactory. However, for use in large scale hydrologic modeling or global circulation models, a method to account for the topographic effects must be included in the kriged ETr estimates. A method that might prove successful is developing a spatial correlation between ETr and elevation through a geostatistical technique termed cokriging.

Another problem with the regional analysis was comparison at regional boundaries. It was difficult to compare contours across climatic regions because the contour lines were not coincident. To effectively utilize these contour maps for the whole state, there must be some method to deal with the transition zones between regions. A possibility is to combine kriged estimates from each region into one file representing the whole state and producing contour plots for the overall data file.

It is not difficult to see the usefulness of computerized plots of reference evapotranspiration in water resources management. Geostatistics is one possible tool to generate these estimates and plots. There are indeed difficulties to overcome for geostatistics to be applied operationally in estimating regional evapotranspiration. However, the use of geostatistics is becoming more common in hydrology and its use is expected to grow.

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## APPENDICES



**APPENDIX A: Primary Weather Data**

List of the stations included in this study with information about their location, latitude, longitude and site, area, region and cumulative aridities.

R	STN	Station name	Lat (deg)	Long (deg)	Elev (m)	Aridity (%)			
						S	A	R	C
5	0036	Adel	42.18	119.90	1396	100	80	100	90
5	0118	Alkali Lake	42.97	120.00	1320	100	50	80	73
5	0189	Andrews Weston Mine	42.55	118.55	1457	100	100	100	100
4	0197	Antelope	44.92	120.72	817	100	50	50	70
4	0265	Arlington	45.72	120.20	88	30	50	30	40
3	0304	Ashland	42.22	122.72	543	30	50	50	42
1	0328	Astoria Airport	46.15	123.88	3	30	30	0	27
4	0356	Austin	44.58	118.50	1283	30	30	20	29
4	0412	Baker Airport	44.83	117.82	1027	30	10	20	19
1	0471	Bandon	43.15	124.40	6	90	10	10	42
5	0501	Barnes Station	43.95	120.22	1210	90	80	80	84
2	0595	Beaverton	45.50	122.82	67	30	20	20	24
5	0694	Bend	44.07	121.32	1113	70	70	90	72
5	0723	Beulah	43.92	118.17	997	10	50	90	38
4	0858	Boardman	45.83	119.70	91	10	20	20	16
2	0897	Bonneville Dam	45.63	121.95	18	10	10	10	10
1	1055	Brookings	42.05	124.28	21	10	10	0	9
5	1067	Brothers	43.80	120.60	1414	90	90	90	90
5	1174	Burns Junction	42.78	117.85	1198	90	100	100	96
5	1175	Burns Airport	43.58	118.95	1262	70	70	80	71
2	1433	Cascadia	44.40	122.48	262	0	0	0	0
3	1448	Cave Junction	42.17	123.67	390	10	30	30	22
5	1546	Chemult	43.23	121.78	1451	80	60	60	68
5	1574	Chiloquin	42.65	121.95	1268	10	50	50	34
2	1643	Clatskanie	46.10	123.28	27	10	0	0	4
1	1682	Cloverdale	45.22	123.90	24	10	10	10	10
4	1765	Condon	45.23	120.18	863	10	70	80	47
1	1836	Coquille City	43.18	124.20	6	10	10	10	10
2	1862	Corvallis OSU	44.63	123.20	70	10	10	10	10
2	1877	Corvallis Water Bureau	44.52	123.45	180	10	10	10	10
2	1897	Cottage Grove	43.78	123.07	198	10	20	20	16
2	1902	Cottage Grove Dam	43.72	123.05	253	90	20	20	48

R	STN	Station name	Lat (deg)	Long (deg)	Elev (m)	Aridity (%)			
						S	A	R	C
4	1924	Cove	45.30	117.80	890	90	20	10	47
5	1946	Crater Lake	42.90	122.13	1975	50	20	10	17
2	2112	Dallas	44.95	123.28	88	80	20	30	45
5	2135	Danner	42.93	117.33	1289	80	60	60	68
4	2173	Dayville	44.55	119.65	689	80	80	70	79
2	2292	Detroit Dam	44.72	122.25	372	80	30	20	49
1	2370	Dora	43.17	124.00	274	20	30	20	25
2	2374	Dorena Dam	43.78	122.97	250	20	40	20	30
2	2406	Drain	43.67	123.32	88	20	40	30	31
5	2415	Drewsey	43.80	118.38	1073	80	40	30	55
4	2440	Dufur	45.45	121.13	405	80	30	20	49
4	2597	Elgin	45.57	117.92	811	20	20	20	20
1	2633	Elkton	43.60	123.58	37	20	30	20	25
4	2675	Enterprise 2	45.40	117.27	1183	20	30	20	30
4	2678	Enterprise 20	45.70	117.15	1000	20	40	20	30
2	2693	Estacada	45.27	122.32	125	80	40	30	55
2	2709	Eugene Airport	44.12	123.22	110	10	10	10	10
1	2805	Falls City	44.85	123.43	134	10	40	30	27
2	2867	Fernridge Dam	44.12	123.30	149	80	10	10	38
2	2997	Forest Grove	45.53	123.10	55	20	40	30	31
4	3038	Fossil	45.00	120.22	808	20	40	30	31
2	3047	Foster Dam	44.42	122.67	168	80	40	30	55
5	3095	Fremont	43.33	121.17	1375	80	50	60	63
1	3193	Gardiner	43.73	124.30	5	10	10	10	10
1	3356	Gold Beach Ranger Stn.	42.40	124.42	15	20	30	20	25
2	3402	Government Camp	45.30	121.75	1213	20	10	10	14
3	3445	Grants Pass	42.43	123.32	283	80	50	60	63
4	3542	Grizzly	44.52	120.93	1109	20	30	20	25
4	3604	Halfway	44.88	117.12	814	20	40	30	31
5	3692	Hart Mountain Ref.	42.55	119.65	1713	80	80	70	79
2	3770	Hwks Portland Wtr. Bu.	45.45	122.15	229	90	10	40	45
4	3827	Heppner	45.37	119.55	576	80	90	80	85
4	3847	Hermiston	45.82	119.28	189	10	40	30	27
2	3908	Hillsboro	45.52	122.98	49	80	30	20	49
1	3995	Honeyman State Park	43.93	124.10	37	20	20	20	20
4	4003	Hood River Exp. Stn.	45.68	121.52	152	70	20	30	41
3	4060	Howard Prairie Dam	42.22	122.37	1393	80	20	30	45
4	4098	Huntington	44.35	117.27	649	80	60	70	69
3	4126	Idleyld Park	43.37	122.97	329	20	40	30	31
1	4133	Illahe	42.63	124.05	107	20	30	20	25
5	4175	Ironside	44.32	117.98	1195	20	40	30	31
4	4291	John Day	44.43	118.95	933	80	40	30	55
5	4357	Juntura	43.80	117.93	863	70	60	50	63
4	4411	Kent	45.20	120.70	829	60	70	60	65
5	4506	Klamath Falls	42.20	121.78	1250	50	60	50	55
5	4511	Klamath Falls Agr. Stn.	42.17	121.75	1247	70	60	50	63

R	STN	Station name	Lat (deg)	Long (deg)	Elev (m)	Aridity (%)			
						S	A	R	C
2	4606	La Comb	44.62	122.72	158	20	50	40	37
4	4622	La Grande KTVR	45.32	118.08	841	50	40	30	43
5	4670	Lakeview	42.22	120.37	1457	60	80	100	74
1	4776	Laurel Mountain	44.92	123.57	1094	80	0	10	33
2	4811	Leaburg	44.10	122.68	207	70	50	30	56
3	4835	Lemolo Lake	43.37	122.22	1244	70	0	0	28
4	5020	Long Creek	44.72	119.10	1134	20	50	30	36
2	5050	Lookout Point Dam	43.92	122.77	216	20	40	30	31
3	5055	Lost Creek Dam	42.67	122.68	482	80	40	30	55
4	5139	Madras	44.63	121.13	680	60	50	50	54
4	5142	Madras 2	44.67	121.15	744	80	50	50	62
5	5160	Malheur Ranch Exp. Stn.	43.98	117.02	680	70	30	40	47
5	5162	Malheur Refuge Hdq.	43.28	118.83	1253	80	30	40	51
5	5174	Malin	42.00	121.32	1411	50	40	50	45
4	5258	Mason Dam	44.67	118.00	1189	90	40	40	60
5	5335	Mc Dermitt	42.42	117.87	1359	80	90	90	86
2	5384	Mc Minnville	45.23	123.18	46	20	30	20	25
3	5424	Medford Exp. Stn.	42.30	122.87	445	20	30	40	27
3	5429	Medford Airport	42.37	122.87	399	90	40	40	60
4	5515	Metolius	44.58	121.18	762	20	70	90	52
4	5545	Mikkalo	45.47	120.35	472	60	50	30	52
4	5593	Milton Freewater	45.95	118.42	296	80	50	40	61
4	5610	Minam	45.68	117.60	1100	50	50	40	49
4	5641	Mitchell	44.58	120.18	808	90	80	70	83
4	5711	Monument	44.82	119.42	610	50	70	70	62
4	5734	Moro	45.48	120.72	570	80	70	80	75
1	6032	Newport	44.58	124.05	43	50	10	20	27
1	6073	North Bend Airport	43.42	124.25	3	20	20	20	20
2	6151	No Willamette Exp. Stn.	45.28	122.75	46	80	40	20	54
2	6173	Noti	44.07	123.47	137	20	30	10	24
5	6179	Nyssa	43.87	117.00	664	20	60	70	45
5	6243	Ochoco Ranger Stn.	44.40	120.43	1213	20	40	50	33
5	6252	Odell Lake East	43.55	121.97	1463	20	30	50	28
5	6294	Ontario KSRV	44.05	116.97	655	80	50	40	61
5	6302	OO Ranch	43.28	119.32	1262	60	50	70	56
2	6334	Oregon City	45.35	122.60	52	50	20	20	32
1	6366	Otis	45.03	123.93	46	20	30	20	25
5	6405	Owyhee Dam	43.65	117.25	732	60	30	70	46
5	6426	Paisley	42.70	120.53	1329	20	60	70	45
4	6466	Parkdale	45.53	121.57	463	20	30	30	26
5	6500	Paulina	44.13	119.97	1122	60	50	60	55
4	6532	Pelton Dam	44.73	121.23	430	80	30	40	51
4	6540	Pendleton Exp. Stn.	45.72	118.63	454	60	80	70	71
4	6541	Pendleton Roundup Park	45.67	118.80	322	20	80	70	55
4	6546	Pendleton Airport	45.68	118.85	454	20	80	70	55
4	6634	Pilot Rock	45.48	118.82	524	60	80	70	71

R	STN	Station name	Lat (deg)	Long (deg)	Elev (m)	Aridity (%)			
						S	A	R	C
4	6655	Pine Grove	45.12	121.37	677	60	70	60	65
2	6749	Portland KGW-TV	45.52	122.68	49	70	60	30	61
2	6751	Portland Airport	45.60	122.60	6	80	60	30	65
1	6784	Port Orford	42.75	124.50	15	20	20	10	19
1	6820	Powers	42.88	124.07	70	20	40	30	31
5	6853	P Ranch Refuge	42.82	118.88	1280	20	80	70	55
5	6883	Prineville	44.35	120.90	866	60	50	50	54
3	6907	Prospect	42.73	122.52	756	90	40	60	62
5	7056	Redmond	44.27	121.17	920	20	60	70	45
5	7062	Redmond Airport	44.27	121.15	933	70	60	70	65
4	7160	Richland	44.77	117.17	677	60	40	30	47
3	7169	Riddle	42.95	123.35	207	20	40	30	31
5	7208	Riverside	43.50	118.07	914	90	50	90	70
5	7277	Rocksville	43.37	117.12	1119	20	60	80	46
5	7310	Rome	42.87	117.65	1039	80	40	80	60
3	7331	Roseburg KQEN	43.20	123.35	143	60	60	70	61
5	7354	Round Grove	42.33	120.88	1490	60	50	60	55
3	7391	Ruch	42.23	123.03	472	20	30	40	27
2	7466	St Helens RFD	45.87	122.82	30	20	40	20	30
2	7500	Salem	44.92	123.02	61	20	10	10	14
2	7586	Scoggins Dam	45.48	123.20	110	80	30	20	49
2	7631	Scotts Mills	44.95	122.53	707	20	40	30	31
1	7641	Seaside	45.98	123.92	3	60	10	10	30
5	7675	Seneca	44.13	118.97	1420	70	50	30	56
3	7698	Sexton Summit	42.62	123.37	1170	20	50	60	39
5	7736	Sheaville	43.12	117.03	1408	50	70	80	63
2	7809	Silver Creek Falls	44.87	122.65	411	20	30	20	25
5	7817	Silver Lake	43.12	121.07	1335	50	30	60	41
2	7823	Silverton	45.00	122.77	125	80	50	40	61
5	7857	Sisters	44.30	121.55	969	80	60	60	68
5	8007	Sprague River	42.45	121.50	1329	80	20	50	47
5	8029	Squaw Butte Exp. Stn.	43.48	119.72	1420	80	80	80	80
2	8095	Stayton	44.78	122.82	131	20	30	20	25
5	8173	Summer Lake	42.95	120.78	1277	60	30	80	47
5	8250	Suntex	43.60	119.63	1314	20	70	80	51
4	8407	The Dalles	45.60	121.20	30	60	50	40	53
5	8420	The Poplars	43.27	120.93	1317	20	40	60	34
2	8466	Three Lynx	45.12	122.07	341	60	20	30	37
1	8481	Tidewater	44.42	123.90	15	20	30	20	25
1	8494	Tillamook	45.45	123.87	3	20	40	30	31
3	8536	Toketee Falls	43.28	122.45	628	80	30	40	51
2	8634	Troutdale	45.55	122.40	9	80	20	20	44
4	8726	Ukiah	45.13	118.93	1024	20	40	40	32
4	8746	Union Exp. Stn.	45.22	117.88	844	20	20	20	20
4	8780	Unity	44.43	118.23	1228	90	40	20	58
5	8797	Vale	43.98	117.25	683	80	40	50	57

R	STN	Station name	Lat (deg)	Long (deg)	Elev (m)	Aridity (%)			
						S	A	R	C
5	8812	Valley Falls	42.48	120.28	1320	60	80	100	74
1	8833	Valsetz	44.85	123.67	354	60	40	10	45
2	8884	Vernonia	45.87	123.18	192	50	40	20	42
5	8948	Wagontire	43.25	119.88	1442	60	50	80	57
4	8985	Walla Walla	46.00	118.05	732	20	40	40	32
4	8997	Wallowa	45.56	117.53	890	50	40	20	42
5	9176	Westfall	44.05	117.75	957	60	70	80	67
5	9290	Whitehorse Ranch	42.33	118.23	1280	20	70	80	51
5	9316	Wickiup Dam	43.68	121.68	1329	80	30	60	53
3	9464	Winchester	43.28	123.42	140	50	50	50	50

## APPENDIX B: Secondary Weather Data

Sources of minimum air relative humidity (or related variables) at the different SWD stations.

Station name	ODD DATA BASE Daily values Min. rel. hum., %	DHA DATA BASE Hourly values Avg. rel. hum., %	CHDD DATA BASE Daily values Dewp. temp., °F	PNHH DATA BASE Hourly values Min. rel. hum., %	Recommended source
Astoria	16 years 1953-1987	31 years 1953-1983		5 years 1953-1957	ODD
Baker		17 years 1948-1964		10 years 1948-1957	DHA
Boardman			2-5 years 1984-1988		CHDD
Boise, ID		36 years 1948-1983		10 years 1949-1958	DHA
Burns	3-4 years 1984-1987	33 years 1948-1980		11 years 1948-1958	DHA
Eugene	10-12 years 1948-1987	36 years 1948-1983		11 years 1948-1958	ODD
Hermiston			1-9 years 1980-1988		CHDD
Klamath Falls		23 years 1948-1970		10 years 1949-1958	DHA
La Grande				6 years 1948-1953	PNHH
Meacham				10 years 1950-1959	PNHH
Medford	20-21 years 1948-1987	36 years 1948-1983		10 years 1949-1958	ODD
North Bend		31 years 1948-1978		10 years 1950-1959	DHA
Ontario				7 years 1948-1954	PNHH
Pendleton	20-21 years 1948-1987	46 years 1938-1983		10 years 1949-1958	ODD
Portland	20-21 years 1948-1987	37 years 1948-1984		10 years 1949-1958	ODD
Redmond		36 years 1948-1983		10 years 1949-1958	DHA
Roseburg		17 years 1948-1964		5 years 1953-1957	DHA
Salem	20-21 years 1948-1987	38 years 1948-1985		10 years 1949-1958	ODD
Sexton Summit	4-5 years 1948-1987	31 years 1948-1978		10 years 1950-1959	DHA
The Dalles		17 years 1948-1964			DHA
Walla Walla		18 years 1948-1965		10 years 1949-1958	DHA

1. Digital Daily Data (ODD)
2. Digital Hourly Airport Data (DHA)
3. Hermiston Digital Daily Data (CHDD)
4. Published Hourly Airport Data (PNHH)



Sources of ratio of actual to maximum possible sunshine hours (or related variables) at the different SWD stations.

Station name	ODD DATA BASE Daily values Daytime cloud cover*	DHA DATA BASE Hourly values Cloud cover	CHDD DATA BASE Daily values Meas. solar rad. cal cm <sup>-2</sup> d <sup>-1</sup>	PMA DATA BASE Monthly values Daytime cloud cover*	ASSR DATA BASE Monthly values Meas. solar rad. kW h m <sup>-2</sup>	PNSR DATA BASE Monthly values Est. solar rad.** cal cm <sup>-2</sup> d <sup>-1</sup>	Recommended source
Astoria	23 years 1965-1987	31 years 1953-1983		35 years 1953-1987		5-10 years** 1948-1970	PNSR
Baker		17 years 1948-1964				5-10 years 1948-1970	DHA
Bend					7 years 1977-1983		ASSR
Boardman			5 years 1984-1988				CHDD
Boise, ID		36 years 1948-1983					DHA
Burns	7-8 years 1980-1987	33 years 1948-1980					ODD
Coos Bay					7 years 1977-1983		ASSR
Corvallis						5-10 years** 1948-1970	PNSR
Eugene	23 years 1965-1987	36 years 1948-1983		38 years 1949-1986	9 years 1975-1983	5-10 years 1948-1970	ASSR
Hermiston			9 years 1980-1988		5 years 1979-1983		CHDD
Klamath Falls		23 years 1948-1970				5-10 years 1948-1970	DHA
La Grande					7 years 1977-1983	5-10 years 1948-1970	ASSR
Meacham						5-10 years 1948-1970	PNSR

Station name	ODD DATA BASE Daily values Daytime cloud cover*	DHA DATA BASE Hourly values Cloud cover	CHDD DATA BASE Daily values Meas. solar rad. cal cm <sup>-2</sup> d <sup>-1</sup>	PMA DATA BASE Monthly values Daytime cloud cover*	ASSR DATA BASE Monthly values Meas. solar rad. kW h m <sup>-2</sup>	PNSR DATA BASE Monthly values Est. solar rad.** cal cm <sup>-2</sup> d <sup>-1</sup>	Recommended source
Medford	23 years 1965-1987	36 years 1948-1983				5-10 years** 1948-1970	PNSR
Mountain Home, ID						5-10 years 1948-1970	PNSR
Ontario						5-10 years 1948-1970	PNSR
Pendleton	23 years 1965-1987	46 years 1938-1983		35 years 1949-1983		5-10 years 1948-1970	ODD
Portland	23 years* 1965-1987	37 years 1948-1984		38 years* 1949-1986	4 years 1980-1983	5-10 years 1948-1970	ODD
Redmond		36 years 1948-1983				5-10 years 1948-1970	DHA
Roseburg		17 years 1948-1964				5-10 years 1948-1970	DHA
Salem	23 years 1965-1987	38 years 1948-1985					ODD
Sexton Summit	22-23 years 1965-1987	31 years 1948-1978		31 years 1948-1976; 1982-1984		5-10 years 1948-1970	ODD
The Dalles		17 years 1948-1964)				5-10 years 1948-1970	DHA
Walla Walla		18 years 1948-1965					DHA
Whitehorse Ranch					7 years 1977-1983		ASSR

\* Ratio of actual to maximum possible sunshine hours were measured.

\*\* Solar radiation was measured.

1. Digital Daily Data (ODD)
2. Digital Hourly Airport Data (DHA)
3. Monthly Average Data (PMA)
4. Published Estimated/Measured Solar Radiation (PNSR)
5. Atmospheric Sciences Solar Radiation Data (ASSR)
6. Hermiston Digital Daily Data (CHDD)

Sources of daytime windspeed (or related variables) at the different SWD stations.

Station name	ODD DATA BASE Daily values Avg. windspeed mph x 10	DHA DATA BASE Hourly values Avg. windspeed knots x 10	CHDD DATA BASE Daily values Total windrun mi	PNHH DATA BASE Hourly values Avg. windspeed mph	PMA DATA BASE Monthly values Avg. windspeed mph	WRPE DATA BASE Monthly values Total windrun mi	Recommended source
Astoria	4 years 1984-1987	31 years 1953-1983		5 years 1953-1957	34 years 1953-1986	5-7 years 1966-1973	DHA
Baker		17 years 1948-1964		10 years 1948-1957			DHA
Boardman			2-5 years 1984-1988				CHDD
Boise, ID		36 years 1948-1983					DHA
Burns	3-4 years 1984-1987	33 years 1948-1980		11 years 1948-1958			DHA
Corvallis						3-21 years 1966-1987	WRPE
Cottage Grove Dam						12-13 years 1966-1978	WRPE
Detroit Dam						3-22 years 1966-1987	WRPE
Eugene	4 years 1984-1987	36 years 1948-1983		11 years 1948-1958	36 years 1949-1984		DHA
Hermiston			8-9 years 1980-1988			10-19 years 1966-1987	CHDD
Klamath Falls		23 years 1948-1970		10 years 1949-1958		5-10 years 1978-1987	DHA
La Grande				6 years 1948-1953			PNHH
Lookout Point Dam						8-22 years 1966-1987	WRPE
Madras						4-14 years 1974-1987	WRPE
Malheur Refuge Hdq						4-17 years 1966-1987	WRPE
Mechan				10 years 1950-1959			PNHH
Medford	4 years 1984-1987	36 years 1948-1983		10 years 1949-1958	36 years 1949-1984	3-21 years 1966-1987	DHA
Moro						17-22 years 1966-1987	WRPE
No Willamette Exp. Stn.						15-22 years 1966-1987	WRPE
North Bend		31 years 1948-1978		10 years 1950-1959			DHA
Ontario				7 years 1948-1954			PNHH
Pendleton	4 years 1984-1987	46 years 1938-1983		10 years 1949-1958	35 years 1949-1983	12-13 years 1975-1987	DHA
Portland	4 years 1984-1987	37 years 1948-1984		10 years 1949-1958	38 years 1949-1986		DHA
Redmond		36 years 1948-1983		10 years 1949-1958			DHA
Roseburg		17 years 1948-1964		5 years 1953-1957			DHA
Salem	4 years 1984-1987	38 years 1948-1985		10 years 1949-1958	40 years 1949-1988		DHA

Station name	ODD DATA BASE Daily values Avg. windspeed mph x 10	DHA DATA BASE Hourly values Avg. windspeed knots x 10	CHDD DATA BASE Daily values Total windrun mi	PNHH DATA BASE Hourly values Avg. windspeed mph	PMA DATA BASE Monthly values Avg. windspeed mph	WRPE DATA BASE Monthly values Total windrun mi	Recommended source
Sexton Summit	4 years 1984-1987	31 years 1948-1978		10 years 1950-1959			DHA
Summer Lake						21-22 years 1966-1987	WRPE
The Dalles		17 years 1948-1964					DHA
Walla Walla		18 years 1948-1965					DHA
Warm Springs Reservoir						6-9 years 1966-1974	WRPE
Wickiup Dam						9-22 years 1966-1987	WRPE

1. Digital Daily Data (ODD)
2. Digital Hourly Airport Data (DHA)
3. Monthly Average Data (PMA)
4. Windrun (Pan Evaporimeter Height) Data (WRPE)
5. Hermiston Digital Daily Data (CHDD)
6. Published Hourly Airport Data (PNHH)

**APPENDIX C: Cropmir Program Listing**

CROPMIR v. 1.0

GENERAL PROGRAM TO ESTIMATE MONTHLY CROP WATER USE AND  
CROP IRRIGATION REQUIREMENTS

METHODS: - Crop water use

a) FAO Blaney-Criddle w/ USDA adjustments  
b) FAO crop coefficients

- Effective precipitation:

Soil Conservation Service method

AUTHORS: Antonio Martinez-Cob  
Gabriel Katul  
Jeffery L. Nuss

Water Resources Team  
Dept. of Agricultural Engineering  
Oregon State University  
Corvallis, Oregon

MAIN MODULE

```

/      ----  Declare subroutines and libraries
DECLARE SUB BLACRI ( )           / ----  ETo (Blaney-Criddle) by stations
DECLARE SUB REGETO ( )          / ----  ETo (Blaney-Criddle) by regions
DECLARE SUB MONTHIR ( )         / ----  Monthly IR for each year of record (by regions)
DECLARE SUB DISTRIB ( )         / ----  Distribution of monthly ET crop and monthly IR
DECLARE SUB FINISH ( )          / ----  Warning when a subroutine is finished
DECLARE SUB SCRCLEAN ( )        / ----  Clean screen, except borders
REM $INCLUDE: 'c:\qb45\WRET.ICL' / ----  Useful function library

/      ----  Main menu
10  CLS
    BOX 5, 79, 2, 23, 2           / ----  Borders of the screen
    LOCATE 2, 39: COLOR 0, 7: PRINT " MENU ": COLOR 7, 0
    LOCATE 23, 35: COLOR 0, 7: PRINT " CROPMIR v. 1.0 ": COLOR 7, 0
    LOCATE 6, 10: COLOR 0, 7: PRINT " 1 "; : COLOR 7, 0
    PRINT " Monthly reference ET by met. stations"
    LOCATE 8, 10: COLOR 0, 7: PRINT " 2 "; : COLOR 7, 0
    PRINT " Monthly ref. ET & secondary weather data by climatic regions"
    LOCATE 10, 10: COLOR 0, 7: PRINT " 3 "; : COLOR 7, 0
    PRINT " Monthly crop ET & net IR by climatic regions"
    LOCATE 12, 10: COLOR 0, 7: PRINT " 4 "; : COLOR 7, 0
    PRINT " Distribution of monthly crop ET & net IR by climatic regions"
    LOCATE 14, 10: COLOR 0, 7: PRINT " 5 "; : COLOR 7, 0
    PRINT " Quit the program"
    LOCATE 17, 10: PRINT "Enter your selection < 1, 2, 3, 4, or 5 >"
    LOCATE 19, 15: INPUT " ", MENU
    SELECT CASE MENU
        CASE 1: CALL BLACRI
        CASE 2: CALL REGETO
        CASE 3: CALL MONTHIR
        CASE 4: CALL DISTRIB
        CASE 5: GOTO 20
        CASE ELSE: BEEP
    END SELECT: GOTO 10

/      ----  Quit the program
20  CALL SCRCLEAN           / ----  Clean screen, except borders
    LOCATE 10, 25: INPUT "Are you sure (y/n) ", QUIT$
    IF UCASE$(QUIT$) = "Y" THEN 30
    GOTO 10
30  CLS
    BOX 20, 50, 8, 16, 1
    LOCATE 11, 25: COLOR 31
    PRINT "Hope to see you again"
    LOCATE 14, 25: PRINT "Bye, friend!"

```

```

COLOR 7
LOCATE 23
END

      BLACRI

----- Subroutine to compute monthly ref. ET by stations.
        FAO Blaney-Criddle method with USDA adjustments

SUB BLACRI STATIC

    ----- Dimension variables

DIM REMIN(1 TO 12), UDAY(1 TO 12), SUNSH(1 TO 12), RSOL(1 TO 12)
DIM U24(1 TO 12), U2(1 TO 6), RH(1 TO 6), RAT(1 TO 2, 1 TO 12)
DIM P(1 TO 2, 1 TO 12), LAT(1 TO 2), NR(1 TO 36, 1 TO 6)
DIM BB(1 TO 36, 1 TO 6, 1 TO 6)

    ----- Borders of the screen

CLS
BOX 5, 79, 2, 23, 1
LOCATE 2, 30: COLOR 0, 7: PRINT " MONTHLY REF. ET (STATIONS) ": COLOR 7, 0
LOCATE 23, 35: COLOR 0, 7: PRINT " CROPMIR v. 1.0 ": COLOR 7, 0

    ----- Drive/directory for input and output data files

LOCATE 5, 10: PRINT "Enter drive containing input data files"
LOCATE 7, 10: INPUT "< x:\path\ > ", BCINPD$
LOCATE 10, 10: PRINT "Enter drive to store output data files"
LOCATE 12, 10: INPUT "< x:\path\ > ", BCOUTD$
LOCATE 15, 10: PRINT "Do you wish to correct ETo by elevation"
LOCATE 17, 10: INPUT "< Y / N > ", CORREL$
IF UCASE$(CORREL$) <> "Y" AND UCASE$(CORREL$) <> "N" THEN BEEP: GOTO 1

CALL SCRCLEAN          ' ----- Clean screen, except borders
LOCATE 8, 25: PRINT "Please, wait! ..."
LOCATE 10, 15: PRINT "Computing reference ET by met. stations"
BOX 14, 36, 13, 17, 1
LOCATE 15, 19: PRINT "Station "
BOX 42, 70, 13, 17, 1
LOCATE 15, 47: PRINT "Stations done "

    ----- Open file containing station identification numbers

INFO$ = BCINPD$ + "STNINFTH.DAT"
OPEN "I", #1, INFO$
FOR A = 1 TO 4
    INPUT #1, LL1$
NEXT A
BFLAG = 0: DONESTN = 0
WHILE NOT EOF(1)
    LINE INPUT #1, CODE$
    CODE$ = MID$(CODE$, 3, 4)
    IF CODE$ = "0652" OR CODE$ = "5221" OR CODE$ = "5362" THEN 55
    IF CODE$ = "6213" OR CODE$ = "7554" OR CODE$ = "7559" THEN 55

    LOCATE 15, 28: COLOR 31: PRINT CODE$: COLOR 7
    LOCATE 15, 62: COLOR 31: PRINT DONESTN: COLOR 7

    ----- Determine names of input data files

FILEIN1$ = BCINPD$ + "STN#" + CODE$ + ".PDT"   ' ----- Primary weather
FILEIN2$ = BCINPD$ + "STN#" + CODE$ + ".SDT"   ' ----- Secondary weather

    ----- Determine output file names

FILEOUT$ = BCOUTD$ + "STN#" + CODE$ + ".ETR"
PFLAG = 0: RATFLAG = 0

    ----- Open primary weather data file

OPEN "I", #2, FILEIN1$
INPUT #2, STATCODE, ELEV, LATITUDE$, ARIDRAT
HEMIS$ = RIGHT$(LATITUDE$, 1)
LATITUD = VAL(LATITUDE$)
RANF$ = "RAN": PF$ = "PN"
IF UCASE$(HEMIS$) = "S" THEN RANF$ = "RAS": PF$ = "PS"

```

```

'      ----   Open output files and store heading parameters
OPEN "O", #3, FILEOUT$
PRINT #3, STATCODE
ARIDRAT = ARIDRAT / 100

'      ----   Read secondary weather data
OPEN "I", #7, FILEIN2$
INPUT #7, STATCODE
WHILE NOT EOF(7)
  INPUT #7, MON, RHMIN(MON), RSOL(MON), SUNSH(MON), U24(MON), UDAY(MON)
WEND
CLOSE #7

'      ----   Read primary weather data and estimate ref. ET
WHILE NOT EOF(2)
  INPUT #2, ANNEE, MONTH, TMAX, TMIN
  GOSUB 60 ' ----   Mean daily percentage of annual daytime hours
  GOSUB 100 ' ----   Aridity effects and reference ratios
  ARIDADJ = ARIDRAT * ARID
  TMED = (TMAX + TMIN) / 2 - ARIDADJ
  IF SUNSH(MONTH) > 0 THEN 40
  GOSUB 160 ' ----   Atmospheric solar radiation (mm/d)
  SUNSH(MONTH) = (RSOL(MONTH) / 59) / (.5 * RAAT) - .5
  IF UDAY(MONTH) > 0 THEN 50
  UDAY(MONTH) = U24(MONTH) * (2 / 3) * (1000 / 43200)
  F = P * (.46 * TMED + 8.13)
  A = .0043 * RHMIN(MONTH) - SUNSH(MONTH) - 1.41
  GOSUB 110 ' ----   b coefficient
  IF UCASE$(CORREL$) = "N" THEN ETO = A + B * F: GOTO 52
  ETO = (A + B * F) * (1 + ELEV / 10000)
  ETO = ETO * REFRAT ' ----   Monthly ref. ET, mm/d
  IF ETO < 0 THEN ETO = 0
  IF UCASE$(CORREL$) = "N" THEN 53
  PRINT #3, USING "#### ## ##.##"; ANNEE, MONTH, ETO
  GOTO 54
  PRINT #3, USING "#### ## ##.##"; ANNEE, MONTH, ETO
WEND
CLOSE #2: CLOSE #3
DONESTM = DONESTM + 1
55 WEND
CLOSE #1

CALL SCRCLEAN ' ----   Clean screen, except borders
LOCATE 7, 15: PRINT "Reference ET computed for all met. stations"
CALL FINISH
GOTO 200

'      ----   Mean daily percentage of annual daytime hours
60 IF PFLAG = 1 THEN 90
FCONT = 1
OPEN "I", #4, PF$
FOR LIN = 1 TO 4
  INPUT #4, LIN$ ' ----   Read table headings
NEXT LIN
70 INPUT #4, LAT(FCONT)
FOR MON = 1 TO 12
  INPUT #4, P(FCONT, MON)
NEXT MON
IF LATITUD >= LAT(FCONT) THEN 80
IF (LAT(FCONT) > 40 AND (LATITUD - LAT(FCONT)) >= -2) THEN FCONT = 2
IF (LAT(FCONT) <= 40 AND (LATITUD - LAT(FCONT)) >= -5) THEN FCONT = 2
GOTO 70
80 CLOSE #4
90 P = P(2, MONTH) - (P(2, MONTH) - P(1, MONTH)) * (LATITUD - LAT(2)) / (LAT(1) - LAT(2))
PFLAG = 1
RETURN

'      ----   Aridity effects and reference ratios
100 SELECT CASE MONTH
CASE 1: ARID = 0: REFRAT = 1
CASE 2: ARID = 0: REFRAT = 1
CASE 3: ARID = 0: REFRAT = 1
CASE 4: ARID = 1: REFRAT = 1.21 / 1.15
CASE 5: ARID = 1.5: REFRAT = 1.14 / 1.15
CASE 6: ARID = 2: REFRAT = 1.07 / 1.15
CASE 7: ARID = 3.5: REFRAT = 1.01 / 1.15
CASE 8: ARID = 4.5: REFRAT = 1 / 1.15
CASE 9: ARID = 3: REFRAT = 1.08 / 1.15
CASE 10: ARID = 0: REFRAT = 1.22 / 1.15

```



```

CASE 11: ARID = 0: REFRAT = 1
CASE 12: ARID = 0: REFRAT = 1
END SELECT: RETURN

' ----- Interpolate b coefficient

110 IF BFLAG = 1 THEN 120
OPEN "I", #5, "BTABLE"
FOR LIN = 1 TO 3
  INPUT #5, LIN$ ' ----- Read table headings
NEXT LIN
INPUT #5, LIN$
FOR Y = 1 TO 6
  INPUT #5, RH(Y) ' ----- Six values of relative humidity
NEXT Y
ZZ = 0 ' ----- Set counter to zero
K = 1 ' ----- K = 1 corresponds to U2(1) = 0, and K = 6 to
U2(6) = 10 m/s ' ----- Read 36 lines from the table
FOR Z = 1 TO 36
  ZZ = ZZ + 1
  IF ZZ = 7 THEN K = K + 1: ZZ = 1
  INPUT #5, U2(K) ' ----- First value of each line is Uday
  INPUT #5, NR(ZZ, K) ' ----- Second value of each line is n/N
  FOR Y = 1 TO 6
    INPUT #5, BB(ZZ, Y, K) ' ----- Next 6 values of each line are b coefficients
  NEXT Y
NEXT Z
CLOSE #5
120 BFLAG = 1
IF UDAY(MONTH) < 2 THEN K1 = 1: GOTO 130
IF UDAY(MONTH) < 4 THEN K1 = 2: GOTO 130
IF UDAY(MONTH) < 6 THEN K1 = 3: GOTO 130
IF UDAY(MONTH) < 8 THEN K1 = 4: GOTO 130
K1 = 5
130 K2 = K1 + 1
IF RHMIN(MONTH) <= 20 THEN Y1 = 1: GOTO 140
IF RHMIN(MONTH) <= 40 THEN Y1 = 2: GOTO 140
IF RHMIN(MONTH) <= 60 THEN Y1 = 3: GOTO 140
IF RHMIN(MONTH) <= 80 THEN Y1 = 4: GOTO 140
Y1 = 5
140 Y2 = Y1 + 1
IF SUNSH(MONTH) <= .2 THEN Z1 = 1: GOTO 150
IF SUNSH(MONTH) <= .4 THEN Z1 = 2: GOTO 150
IF SUNSH(MONTH) <= .6 THEN Z1 = 3: GOTO 150
IF SUNSH(MONTH) <= .8 THEN Z1 = 4: GOTO 150
Z1 = 5
150 Z2 = Z1 + 1
B11 = BB(Z1, Y1, K1) + ((SUNSH(MONTH) - NR(Z1, K1)) / .2) * (BB(Z2, Y1, K1) - BB(Z1, Y1,
K1))
B12 = BB(Z1, Y2, K1) + ((SUNSH(MONTH) - NR(Z1, K1)) / .2) * (BB(Z2, Y2, K1) - BB(Z1, Y2,
K1))
B1 = B11 - ((RHMIN(MONTH) - RH(Y1)) / 20) * (B11 - B12)
B21 = BB(Z1, Y1, K2) + ((SUNSH(MONTH) - NR(Z1, K1)) / .2) * (BB(Z2, Y1, K2) - BB(Z1, Y1,
K2))
B22 = BB(Z1, Y2, K2) + ((SUNSH(MONTH) - NR(Z1, K1)) / .2) * (BB(Z2, Y2, K2) - BB(Z1, Y2,
K2))
B2 = B21 - ((RHMIN(MONTH) - RH(Y1)) / 20) * (B21 - B22)
B = B1 + ((UDAY(MONTH) - U2(K1)) / 2) * (B2 - B1)
RETURN

' ----- Interpolate atmospheric radiation

160 IF RATFLAG = 1 THEN 190
FCONT = 1
OPEN "I", #6, "RANF$
FOR LIN = 1 TO 3
  INPUT #6, LIN$ ' ----- Read table headings
NEXT LIN
INPUT #6, LAT
FOR MON = 1 TO 12
  INPUT #6, RAT(FCONT, MON)
NEXT MON
IF (LATITUD - LAT) >= -2 THEN FCONT = 2
IF (LATITUD >= LAT) THEN 180
GOTO 170
180 CLOSE #6
RAAT = RAT(2, MONTH) - (LATITUD - LAT) / 2 * (RAT(2, MONTH) - RAT(1, MONTH))
190 RATFLAG = 1
RETURN

200 END SUB

```

```

      /
      |                                     FINISH
      |
      |----- Warning when ending a specific procedure
      |
      |
SUB FINISH STATIC
LOCATE 9, 15: PRINT "Press any key to go to the main menu"
FOR BPX = 1 TO 3
    BEEP
NEXT BPX
LOCATE , , 0: WHILE INKEY$ = "": WEND

END SUB

```

```

      /
      |                                     SCRCLEAN
      |
      |----- Clean screen, except borders
      |
      |
SUB SCRCLEAN STATIC
FOR I = 3 TO 22
    LOCATE I, 6: PRINT STRING$(72, " ")
NEXT I

END SUB

```