STUDY TO ASSESS ACCURATE SPATIAL RAINFALL DATA IN LAKE NAIVASHA BASIN, KENYA

Anil Kumar Bhandari
March, 2005

Study to assess accurate spatial rainfall data in Lake Naivasha basin, Kenya

by

Anil Kumar Bhandari

Thesis submitted to the International Institute for Geo-information Science and Earth Observation in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation, Specialisation: Watershed Management, Conservation and River Basin Planning

Thesis Assessment Board

Chairman	Prof. dr. ir. Z. Su (WRS/ITC)
External Examinar	Dr. E. O. Seyhan (Free University of Amsterdam)
Primary Supervisor	Drs. R. Becht (WRS/ITC)
Second Supervisor	Prof. Dr. Ir. A. Stein (EOS/ITC)

INTERNATIONAL INSTITUTE FOR GEO-INFORMATION SCIENCE AND EARTH OBSERVATION
ENSCHEDE, THE NETHERLANDS

I will not use data used in the thesis that are owned by ITC or third parties for publishing without written permission of the ITC thesis supervisor.
I certify that although I may have conferred with others in preparing for this assignment, and drawn upon a range of sources cited in this work, the content of this thesis report is my original work.
Signed……………………...

I dedicate this thesis to my brother Nirmal Kumar Bhandari

Abstract

Geostatistic is a useful tool to capitalize spatial correlation between neighbouring observations to predict attribute values at unsampled locations. It was applied to the Lake Naivasha basin to obtain spatio-temporal distribution of rainfall data. The aim of this study was to assess the accurate rainfall data in the Lake Naivasha basin by integrating geostatistic (cokriging) with weather generator model (WXGEN), estimating the long term daily synthetic rainfall data based on the statistical information from the existing daily rainfall data.

Elevations information of the rainfall stations were obtained from Digital elevation model (DEM) using ENVI and ILWIS softwares. Weather generator input parameters (mean, standard deviation, skewness, wet-wet Markov chain probability, wet-dry Markov chain probability and average number of rainy days) were obtained using EXCEL and SPSS softwares.

Cokriging interpolation with elevation was applied to the weather generator input parameters to obtain spatially distributed map. Fourier series approximation was used to determine temporal variability of the weather generator input parameters. Spatio-temporal map was obtained by combining spatially distributed map with temporal distribution information.

Weather generator model (WXGEN) was applied to generate synthetic rainfall data for specific Julian day(s).

Finally, combination of geostatistical prediction technique (cokriging) with weather generator model (WXGEN) can provide better estimation of long term daily synthetic rainfall data useful for hydrological modelling then other conventional methods.

Key words: Digital Elevation Models (DEM), Geostatistic, Cokriging, Weather generator

Acknowledgements

In the first place, I wish to record my deepest and foremost gratitude to my first supervisor Drs. Robert Becht for his untiring and excellent guidance, supervision, invaluable suggestions and critical reviews of my thesis.

My grateful thanks are due to my second supervisor Prof. Dr. Ir. Alfred Stein for his constant support, regular supervision and invaluable suggestions.

It is my pleasure to thank the Government of The Netherlands and ITC in particular for offering me NFP fellowship to pursue my MSc. Studies at ITC.

I express my special thanks and gratitude to Mr. Santosh Mani Nepal for his invaluable help and suggestions.

I am thankful to the entire staff of the ITC with whom I had the privilege of working with during my studies. Special thanks go to Ir. Arno van Lieshout for his help and kind co-operation during my studies at ITC. I wish to thank Dr. Ben Maathuis, Dr. Ambro Gieske, Dr. C. M. M. Mannaerts, Dr. T. H. M. Rientjes, Dr. R. O. Strobl, Ir. Gabrial Parodi for their support during various part of the study. All my colleagues – who gave me a nice company during the study at ITC are also remembered.

Last but not least, my everlasting gratitude goes to my father, mother, father-in-law, mother-in-law, brother, brothers-in-law, sisters, sisters-in-law, wife Sama, daughter Aditi, nieces and nephews, relatives and friends who always encourage me and wish my success.

Table of contents

List of figures

List of tables

List of Appendices

1. Introduction

1.1. Background

A key ingredient to water management system is the good quality of weather data. The weather plays an important factor in hydrological modelling, planning and forecasting. Rainfall data are needed for water resources management and planning. Rainfall is highly variable, both in space and time, throughout the area (catchments). Knowledge of rainfall and runoff is necessary for the prediction and assessment of the effects of droughts and floods, the estimation of groundwater recharge, and in the design and operation of reservoirs and diversions for water supply and power generation. Rainfall data are used in determining long-term trends in rainfall, and in development of rainfall/runoff models that allows prediction of future conditions and detection of water-supply problems.

Rainfall occurs over time periods from minutes to days and weeks and over areas of a few kilometres to hundreds of kilometres. Hence to measure space/time averaged rainfall a dense network of rain gauge is needed. However, in reality the distribution of rain gauges is often too low to cope with the extreme spatial and temporal variation of rainfall, especially in arid and semi-arid regions and through much of the tropics (Barrett and Martin, 1981).

Lake Naivasha basin lies between the two flanks of the Eastern or Gregory Rift Valley, with the Aberdare Mountains and Kinangop plateau on the east and the Mau Escarpment on the west. The highlands surrounding the catchment receive more rain than the lake and valley floor.

It is well known that rainfall observations from relatively isolated rain gauges are rarely representative of rainfall over wider area. The World Meteorological Organization (WMO, 1974) recommended the minimum gauge density of precipitation networks in various geographical regions. For Temperate, Mediterranean and Tropical mountainous region 100-250 km^2 per gauge is recommended (Dingman, 2002). The overall rain gauge density in Naivasha catchment is 290 km^2 per gauge, but large parts have a much lower density (Tessema, 2001).

Understanding rainfall in the tropics is important because of its influence on large scale atmospheric dynamics and its relevance to human life (Barrett and Martin, 1981).

Previous hydrological studies in the basin were hampered by lack of properly distributed spatial inputs (rainfall and topography). Uneven spatial distribution of the rain gages leads to a data scarcity in upper parts of the basin (Muthuwatta, 2004). Therefore, this thesis is devoted to finding the answer related with the spatial variability of the rainfall in the Lake Naivasha catchment.

1.2. Study area

The lake Naivasha basin, stretching over an area of 3200 km^2, lies in the East African Rift valley about 100 km Northwest of Nairobi. Its geographic coordinates are 0^0 00' to 1^0 00' S and 36^0 00' to 36^0 45' E.

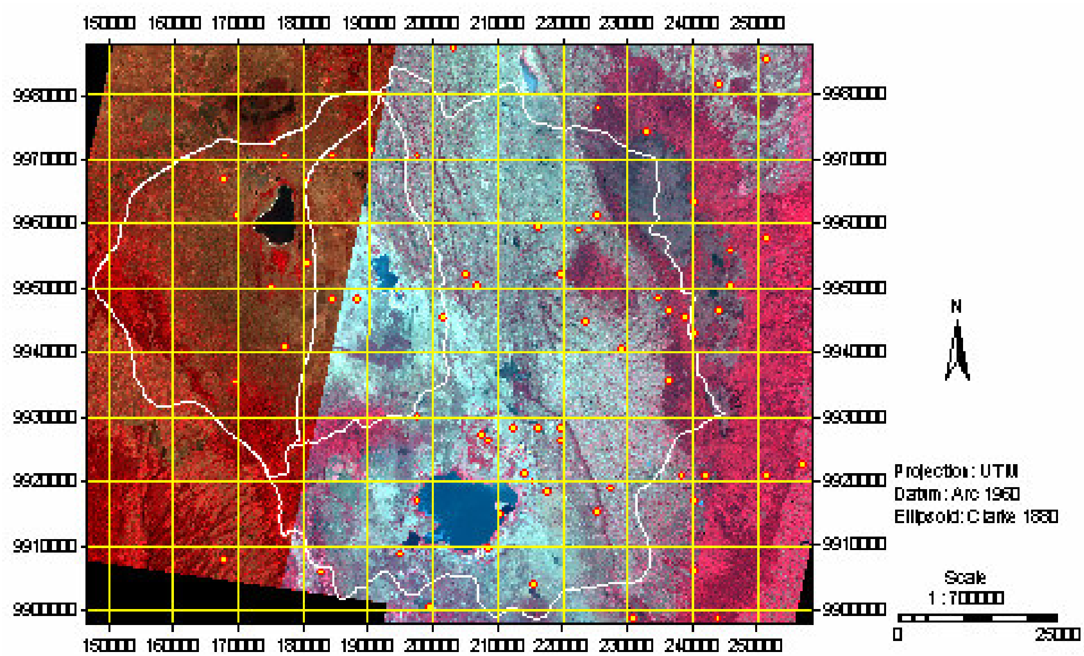


Figure 1-1: The study area and distribution of rain gauges.

It receives an average of 1000 mm of rain per year and it exhibits smooth to very high relief. The area has two distinct rainy season and these are the short rainy season (October to December) and long rainy season (March to June). During the rainy season the major rain bearing system is the squall line: a convective system and moving from east to west.

1.3. Objectives

The objective of the study is to extent the work on synthetic rainfall data to estimate the input parameters for weather generator spatially. In order to achieve this main objective, three sub-objectives will be pursed

- To harmonize rainfall statistics for different time period.
- To interpolate the Weather generator input parameters using Co-kriging.
- To generate time series for 'every point in space' observing the historic rainfall trends.

The objective is justified by assessing accurate spatial distribution of rainfall using temporal and spatial interpolation.

1.4. Research hypotheses

The research hypotheses are:

- It is possible to assess accurate spatial distribution of rainfall using temporal and spatial interpolation.

- Combination of DTM, NDVI time series and MSG-1 data are promising to derive spatially distributed weather generator input parameters.

1.5. Research questions

The research questions are:

- How accurately can weather generator input parameters be spatially and temporally modelled?
- How does spatially correlated weather generator model address the problem of the variation of rainfall data?

1.6. Methodology

Rainfalls vary irregularly in the real world and require appropriate estimation approach for unsampled (or unobserved) points. Geostatistic interpolation technique, such as kriging/cokriging, is used for estimation of rainfall distribution at unsampled points and also in the other field of study (Lang, 2001). Historic rainfall data of stations in and around the basin is used for the study purpose. Prior to analysis it is essential to smooth the data using moving average filter and then it is necessary to verify that the series of data is homogeneous and stationary. Fourier analysis is used to test the homogeneity of the data series. Cokriging interpolation technique is used to interpolate weather generator's input parameters (i.e. mean, standard deviation, skewness, wet-wet Markov chain probability, wet-dry Markov chain probability and average number of rainy days) with elevation. Then those cokriged values and values from optimization from Fourier series are used in deriving spatio-temporal distributed rainfall data in the study area.

1.7. Available data

1.7.1. Digital Elevation Model (DEM)

DEM is defined as digital representation of earth's topography, i.e. an elevation map. DEM is stored in vector or raster format. It can be produced using contour map and satellite or airborne instrument. The satellite or airborne method measures the elevation values directly using a laser or radar altimeter, or Synthetic Aperture Radar (SAR).

The NASA's Shuttle Radar Topography Mission (SRTM) for the first time provides a global high quality Digital Elevation Model (DEM) at resolution levels of 1 and 3 arc sec. The SRTM-DEM cover the earth between latitude 60^0 N and 57^0 S , it is acquired with the same sensor in a single mission and is produced with a single technique-synthetic aperture radar (SAR) interferometry (Rabus et al., 2003). SRTM data provides 90 meters DEM coverage for approx. 80 % of the Earth's land surface. The DEM was created from dual stereoscopic radar signals and post processing.

SRTM generate consistent topographic data to model the terrain. The instrument used is the SAR applying interferometry techniques which allows generation of three dimensional images of the earth's surface. SRTM DEM has been used for research work.

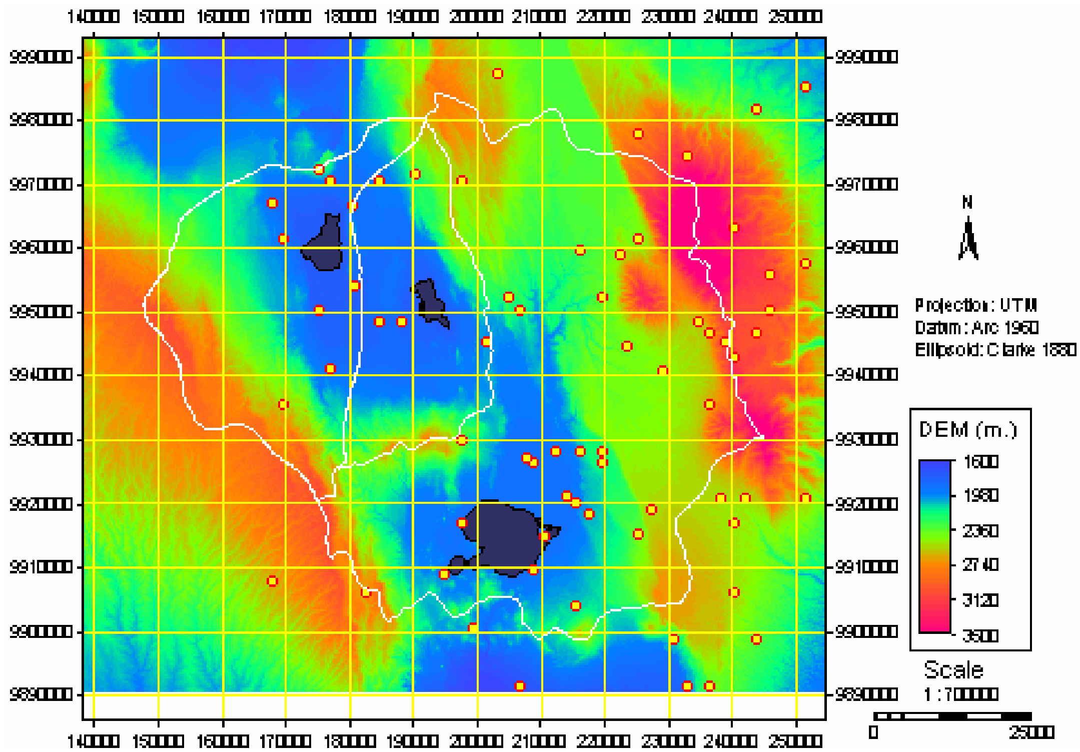


Figure 1-2: SRTM-DEM, catchment boundaries, lakes and distribution of rain gauges.

First the SRTM 90 meters (3 arc second) DEMs were collected from the Africa continent dataset in 1 degree tiles. The tiles obtained were the S01E035, S01E036 and S01E037. The tiles were unzipped before exporting into ENVI, where the DEMs are projected into LatLon WGS84 datum. Then it is imported into ILWIS and converted into UTM datum.

1.7.2. Rainfall stations and rainfall data

Official daily rainfall data records are kept by the Kenya Meteorological Department (KMD). Available rainfall data for the Lake Naivasha basin:

KMD data – The KMD stations in the study area are operated by organizations like Ministry of Environment and Natural Resources (MENR), Forestry Department, Kenya Wildlife Service (KWS), Lake Naivasha Riparian Association (LNRA) and private observers like Cresent Island.

KWS data – Two stations were installed in the Naivasha area (KWS-TI & Hell's Gate N. P.).

LNRA data – The LNRA owns a high quality automatic meteostation (Cambell) located at Loldia farm.

Leicester University data – A high quality automatic station (Delta-T Devices, UK) and a tipping bucket rain gauge was installed at the Elsemere Field Study Centre.

ITC data – In 1999 six automatic rain gauges in the Turasha catchment was installed. In year 2000 two automatic stations were installed at the Mutubio gate to the Aberdares national Park and at Longonot house on Kedong ranch.

Farms data – Several of the larger farms operate (semi) automatic weather stations. Some data is collected by ITC. There is no systematic archiving of these data.

2. Review of techniques in spatial and temporal rainfall estimation

2.1. Measurement of rain with standard rain gauge

Measurement of rainfall by rain gauges gives the rainfall near the earth surface. The measurements are fraught with some problems but it provides the data against which rainfall assessments by other means can be adjusted.

The advantage of using rain gauges to monitor rainfall is (Grimes and Bonafico, 1998):

- Comparability – rainfall amounts can be compared through out a region or over a period of time if standardized gauges are used. Correction factors can be used to take account of difference in design. Comparison between gauge data from different region is possible.
- Simplicity – rain gauges are easily manufactured from local materials and do not require specialized maintenance. Observers can be trained. It is cheap and easy to maintain and read.
- Point measurements – rain gauges measure rainfall at a point but most often the information required is the rainfall average over a large area.
- Availability of data – rain gauge data are available for many years and hence it is possible to do climatological analysis using long period gauge data.
- Distribution of gauges – because gauges usually need to be read at once per day, gauge sites are often dictated by ease of access. This means that there are few gauges in uninhabited areas. Thus the distribution may not be representative of the area as a whole.
- Time delay – rain gauges are typically read at 6 AM to give the previous day's rain. Data are rarely available in a central location on the same day and weeks or even months may elapse before sufficient data are assembled to give a meaning overview.

The disadvantage is:

- It measures point data. Thus, even having a high density of gauge network area estimate of rainfall with reasonable accuracy is difficult to achieve. Moreover, it is impractical and not-cost effective to have a dense network that can measure the highly variable spatial distribution of rainfall.
- Since gauges are read once every month to get real time information they should be located in places where there is easy access for an observer. However, there are remote areas of interest that are difficult to be accesses. Therefore, gauge networks can not cover all area of interest to make a real time observation.
- Source of errors in the reading can easily be occurred due to airflow, unrepresentative orientation and exposure of the gauge, human observation and transmission, evaporation from within the cylinder, gauge leaks and overflow.
- Some times there might be time delay in getting the gauge data at the end of the month.
- On occasions, rain gauges are read during or in between rain events.

- Gauge data at each point is measured by different employees. This increases the observer error.

Of the disadvantages, the first mentioned is the most significant. Particularly in the tropics, rainfall is often localized and a single gauge may only be representative of a very small area in its immediate vicinity on a particular day.

It was found relatively small differences 5% to 10% in the measurements of heavy convective rainfall by pairs of co-located, unshielded rain gauges (Woodley et al., 1974). Deficiencies for rain collected in standard gauges were found to vary from 3% to 30% for annual totals and over a wider range for individual storms (Rodda, 1971).

2.2. Areal rainfall estimation from point data

The accuracy of areal rainfall estimation depends on the spatial variability of precipitation; thus more gauges would be required in those area where rainfall is highly variable, Naivasha basin is of course one of the area where the rainfall is highly variable with space and time.

2.2.1. Isohyetal method

Isohyetal method is based on linear interpolation. Rainfall amounts from a set of gages are plotted on a map of the region. Lines connecting all points of equal precipitation are connected to create an isohyetal map. Isohyets can be drawn by "eyeball". Isohyets divide region into sub-areas.

2.2.2. Thiessen polygon

It is based on the hypothesis that, for every point in the area the best estimate of rainfall is the measurement physically closest to that point. This concept is implemented by drawing perpendicular bisectors to straight lines connecting each two rain gages. This yields, when the watershed boundary is included, a set of closed areas known as Thiessen polygons.

2.2.3. Kriging

Kriging is a method for converting the data into an estimate of the field together with a measure of error or uncertainty. In its simplest form, a kriging estimate of the field at an unobserved location is an optimized linear combination of the data at the observed locations. The coefficients of the kriging estimate and the associated error measure both depend on the spatial configuration of the data, the unobserved location relative to the data locations, and spatial correlation or the degree to which one location can be predicted from a second location as a function of spatial separation.

The measurements are modelled in the following way:

$$z(s_i) = f(s_i) + \varepsilon(s_i), \qquad i = 1,2,....,n$$

Where, in this case, $f(s_i)$ are considered as realizations of random function F in point s_i, which may contain a deterministic function $\mu(s) = E\{F(s)\}$ to model possible trends; $\varepsilon(s_i)$ are realizations of zero mean and uncorrelated random errors. The trend $\mu(s)$ is assumed to be equal to an unknown constant μ.

The spatial correlation between the measured points can be quantified by means of the semivariance function:

$$\gamma(s,h) = \frac{1}{2}\operatorname{var}[F(s) - F(s+h)]$$

Where h is the Euclidean distance between two points. Assume that the trend is constant and γ(s,h) is independent of s. A parametric function is used to model the semivariance for different values of h (Eric et al., 2001).

2.2.4. Regression kriging

Regression kriging is the krig the residuals of a regression model between two variables. (Odeh et al., 1995) compared three forms of regression-kriging (comparable with kriging with external drift). The idea of regression kriging is that the trend component $\mu(s)$ of the model from the random function $F(s)$ as an unknown linear combination of known functions (regression model). In the form of universal kriging the trend component is modelled as a polynomial of certain degree as:

$$\alpha + \beta q(s)$$

The interpolated value at location s_0 can be calculated by a linear combination of the regression model and a weighted sum of regression residuals

$$z^*(s_i) = z(s_i) - \hat{\alpha} - \hat{\beta} q(s_i)$$

This results in:

$$\hat{f}(s_0) = \hat{\alpha} + \hat{\beta} q(s_0) + \sum_{i=1}^{n} w_i z^*(s_i)$$

In the regression kriging, the parameters of the regression model and the parameters of the semivariance function of the spatial correlation regression residuals should be estimated simultaneously. Under the assumption of normality, the parameters can be estimated by restricted maximum likelihood (REML), which is one of the techniques to estimate the parameters of the regression model and the parameters of the semivariance function simultaneously (Eric et al., 2001).

2.2.5. Cokriging

Cokriging is a method for estimation that minimizes the variance of the estimation error by exploiting the cross-correlation between several variables; the estimates are derived using secondary variables as well as the primary variable (Isaaks and Srivastava, 1989).

Cokriging calculates estimates or predictions for a poorly sampled variable (the predictand) with help of a well sampled variable (the covariable). The variable should be highly correlated (positive or negative).

Situation for cokriging:

- A variable is poorly sampled but correlates highly with a second variable that is much better sampled (also better in the sense of more precise). One can take advantage of this correlation to improve estimation of the under sampled variable.
- A variable exhibits low spatial correlation, but correlates highly with the one that shows relatively high continuity.
- The observed values of the second variable may help to improve estimates (predictions) of the first variable, particularly if the first one is under sampled.

Cokriging makes use of different variables, modelled as realizations of stochastic variables. In this study, elevation - Q(s) – of the area D is used as covariable to predict values of precipitation. The spatial dependence is characterized by two semivariance functions γzz(s,h),qq(s,h) and the cross-semivariance function:

$$\gamma_{zq}(s,h) = \frac{1}{2} E\{[Z(s) - Z(s+h)][Q(s) - Q(s+h)]\}$$

To ensure that the variance of any possible linear combination of the two stochastic variables is positive, a so called linear model of co-regionalization is applied. This model implies that each semivariance and cross-semivariance function must be modelled by the same linear combination of semivariance functions (Isaaks and Srivastava, 1989). Furthermore, the matrix of coregionalization should be positive semi-definite. A nested semivariance function is used with a nugget and two spherical semivariance functions with different ranges. The cross-semivariance function can be estimated by the empirical cross-semivariance function.

$$\hat{\gamma}_{zq}(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [z(s_i) - z(s_i + h)][q(s_i) - q(s_i + h)]$$

Where n(h) is the number of data pairs where both variables are measured at an Euclidean distance h. The interpolated value at an arbitrary point s_0 in D is the realization of the (locally) best linear unbiased predictor (BLUP) of $F(s_0)$ and can be written as weighted sum of the measurements:

$$\hat{f}(s_0) = \sum_{i=1}^{m1} w_{1i} z(s_i) + \sum_{j-1}^{m2} w_{2j} q(s_j)$$

Where m_1 is the number of measurements of Z(s) taken within a radius from s_0 (out of the modelling data set), m_2 are the number of meteorological stations certain radius from s_0 (out of the modelling data set). The weights w_{1i} and w_{2j} can be determined using the two semivariance functions and the cross-semivariance function (Eric et al., 2001).

2.3. Weather generator

Weather generators have been used extensively in water engineering design and in agricultural, ecosystem and hydrological impact studies as a means of in-filling missing data or for producing indefinitely long synthetic weather data series from finite station records. The main use of stochastic weather generators, however, is in the generation of synthetic daily weather data for climate change scenarios. Most climate change scenarios consist of monthly change with respect to a particular baseline period, whilst many impacts applications require daily weather data. A stochastic weather generator produces artificial time series of weather data of unlimited length for a location based on the statistical characteristics of observed weather at that location. These types of statistical models are generally developed in two steps, with the first step focussing on the modelling of daily precipitation, whilst the second concentrates on the remaining variables of interest, such as maximum and minimum temperature, solar radiation, humidity and wind speed, which are modelled conditional upon precipitation occurrence. For each month different model parameters are used in order to reflect seasonal variations in both the values of the variables themselves and in their cross-correlations, i.e. in the relation between the individual variable over time.

In a ‘Richardson’ type weather generator (e.g. WGEN) precipitation occurrence is modelled using a first-order two-state Markov procedure, which describes two precipitation classes, i.e. wet or dry, and takes into account precipitation occurrence on the previous day only. The Markov process gives information on transition probabilities, e.g. on the probability of a wet day following a dry day or on the probability of a wet day following a wet day, calculated from the observed station data. If precipitation occurs, then the amount of precipitation falling on wet days is determined usually by using a predefined frequency distribution, most commonly the gamma distribution. The remaining climate variables are then calculated based on their correlations with each other and on the wet or dry status of each day.

3. Data processing and methodology

3.1. Method of data collection

Synoptic stations are those which observe and record all the surface meteorological data. These observations include rainfall, temperature, wind speed and direction, relative humidity, solar radiation, clouds, atmospheric pressure, sun shine hours, evaporation and visibility. At present there are 27 synoptic stations in Kenya. Around Naivasha there is only one operational synoptic station installed at Kenya Agricultural Research Institute (KARI). The closest official synoptic station of any duration is in Nakuru. These stations are run by the KMD staff. The overall quality of data has deteriorated since the beginning of the 1970s. Old equipment is used and the observers are unreliable. An observer may go away for one week and report the raingauge reading on return. This may give the impression of one heavy shower instead of one week of rainy days. Also data may just be invented.

Rainfall stations are those which measure and record daily rainfall only. There were 2000 rainfall stations in Kenya in the year 1977. However the number of rainfall stations drastically dropped to 1653 by the year 1988 and 1497 by 1990. At present there are only 700 rainfall stations in Kenya (http://www.meteo.go.ke/data/). The KMD has 66 rainfall stations with daily data relevant to the Lake Naivasha basin. Currently 32 stations are operational.

Data is normally received from the stations on a monthly basis and then processed at the Climatological Section, KMD. The data is processed in monthly and long term means. Different data types are computed in different forms. Daily rainfall data is analysed on a monthly basis per station to obtain total rainfall, maximum fall in 24 hours, number of days of hail, rain and thunder storms. (http://www.meteo.go.ke/data/)

3.2. Methods of data processing

3.2.1. Preparation of data

Rainfall data from KMD are stored in one Access database file called ‘Watertaps’ (Rolf de By, 2000) in ITC dataset. In this access file, there are two important tables – ‘Station’ and ‘Mdata’. ‘Station’ table contains a single field for each measuring station, indicating its type with some extra information. It also has an attribute [Include?] that can be set to either Yes or No and indicates whether measurements for that station will be included in the synchronisation analysis or not. Other table, i.e. ‘Mdata’ is far bigger and include all measurements for all stations. It has a station identifier, a time step and a value for each measurement. During data preparation, station information and measurements are added. All data from existing tables are deleted to get new set of measurements. In doing so, the following steps were followed:

- Fields for data measuring stations are added to 'Station' table to include measurements in the database.
- Measurement data information of stations is added in the 'Mdata' table.
- Those added measurement data are then imported into database and is loaded in 'Mdata' table.
- Then query operation is run specifying period of time (date), and a list of measured data in column for each station is generated in chronological order
- Those generated measured data of stations are then imported into EXCEL.

Daily rainfall data were then adjusted station wise in column in EXCEL spreadsheet.

Monthly and annual rainfall data are then calculated using SPSS and EXCEL.

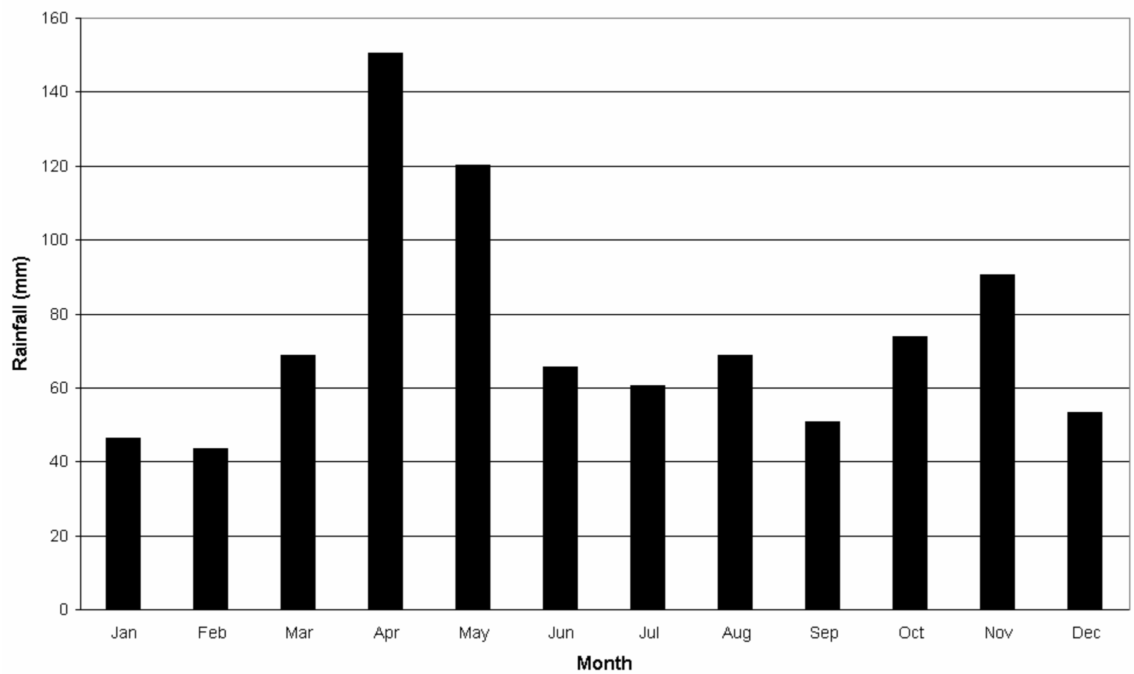


Figure 3-1: Mean monthly rainfall for Lake Naivasha basin using 72 stations (1926-2004).

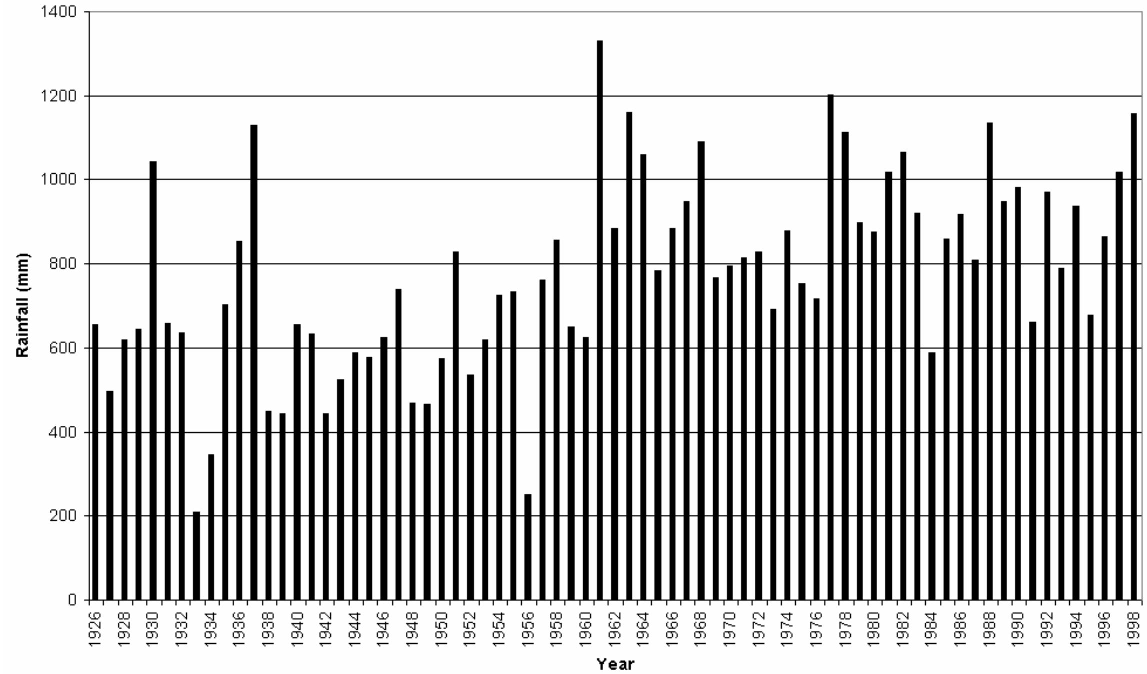


Figure 3-2: Mean annual rainfall for Lake Naivasha basin using 72 stations (1926-1998).

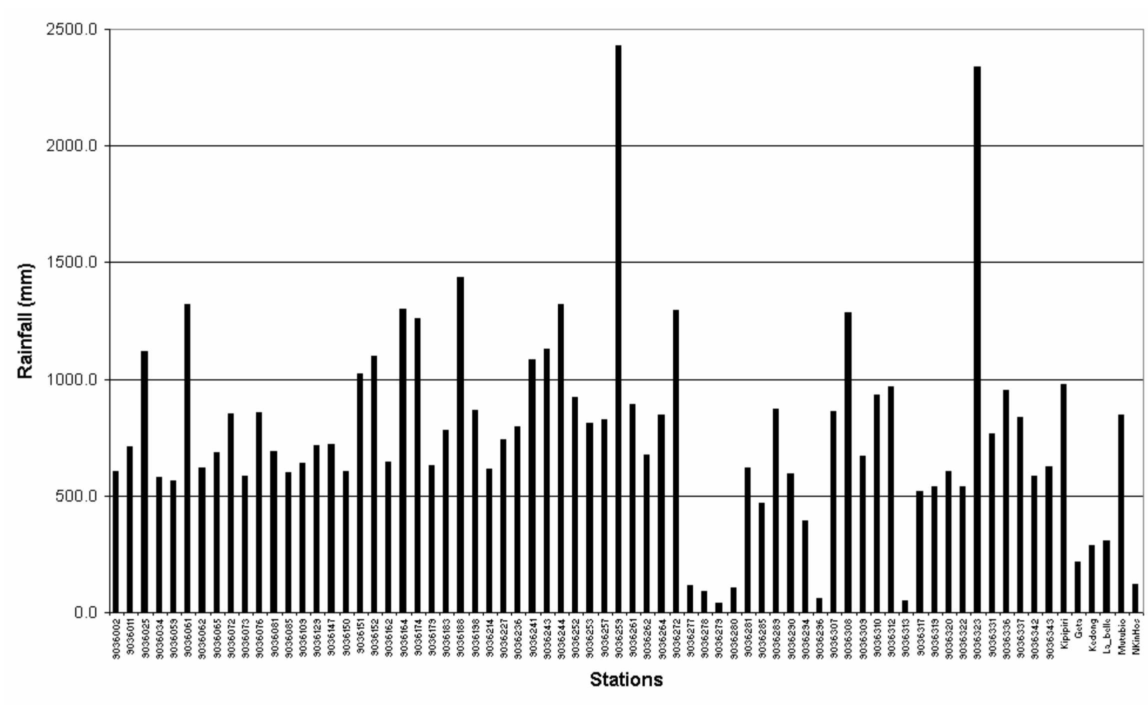


Figure 3-3: Mean annual rainfall of 72 stations, Lake Naivasha basin (1926-2004).

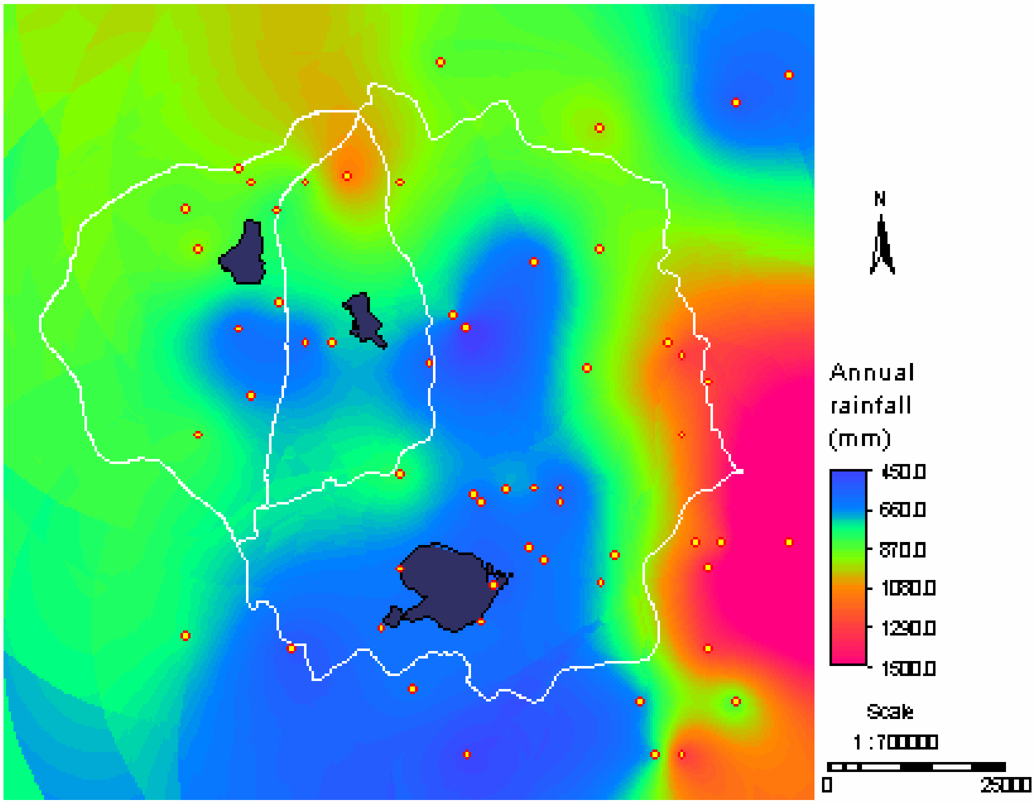


Figure 3-4: Cokriging predicted mean annual rainfall map (showing catchment boundaries, lakes and rain gauge distributions), Lake Naivasha basin.

3.2.2. Data analysis

Rainfall data are analysed to prepare input for cokriging interpolation which is suppose to be used in weather generator model (WXGEN) to get synthetic daily rainfall data. Data from 72 rainfall stations were taken into consideration. Out of it 66 stations were taken from KMD, 5 stations were from data loggers installed by ITC and 1 station was from a local farm. First rainfall station in Lake Naivasha basin was installed in 1926 and other stations were installed in different time frame. It was found that some stations are still operating whilst others ceased operating a long time ago. However, most of the rainfall stations were installed after 1957. Recorded rainfall varies very much in term of years of recording. Considering the quality of data, it was necessary to exclude 12 stations (6 KMD stations, 5 ITC's data loggers and 1 farm data) out of 72 stations for the study purpose.

Status of existing daily rainfall record was calculated from the daily time steps of available data for the study purpose (refer to appendix 2). Table and figure below shows the quality of existing daily rainfall data:

No. of stations	Valid data	Missing data	Total
72	570899 (80%)	140020 (20%)	710919 (100%)

Table 3-1: Status of existing daily rainfall record, Lake Naivasha basin (1926-2004).

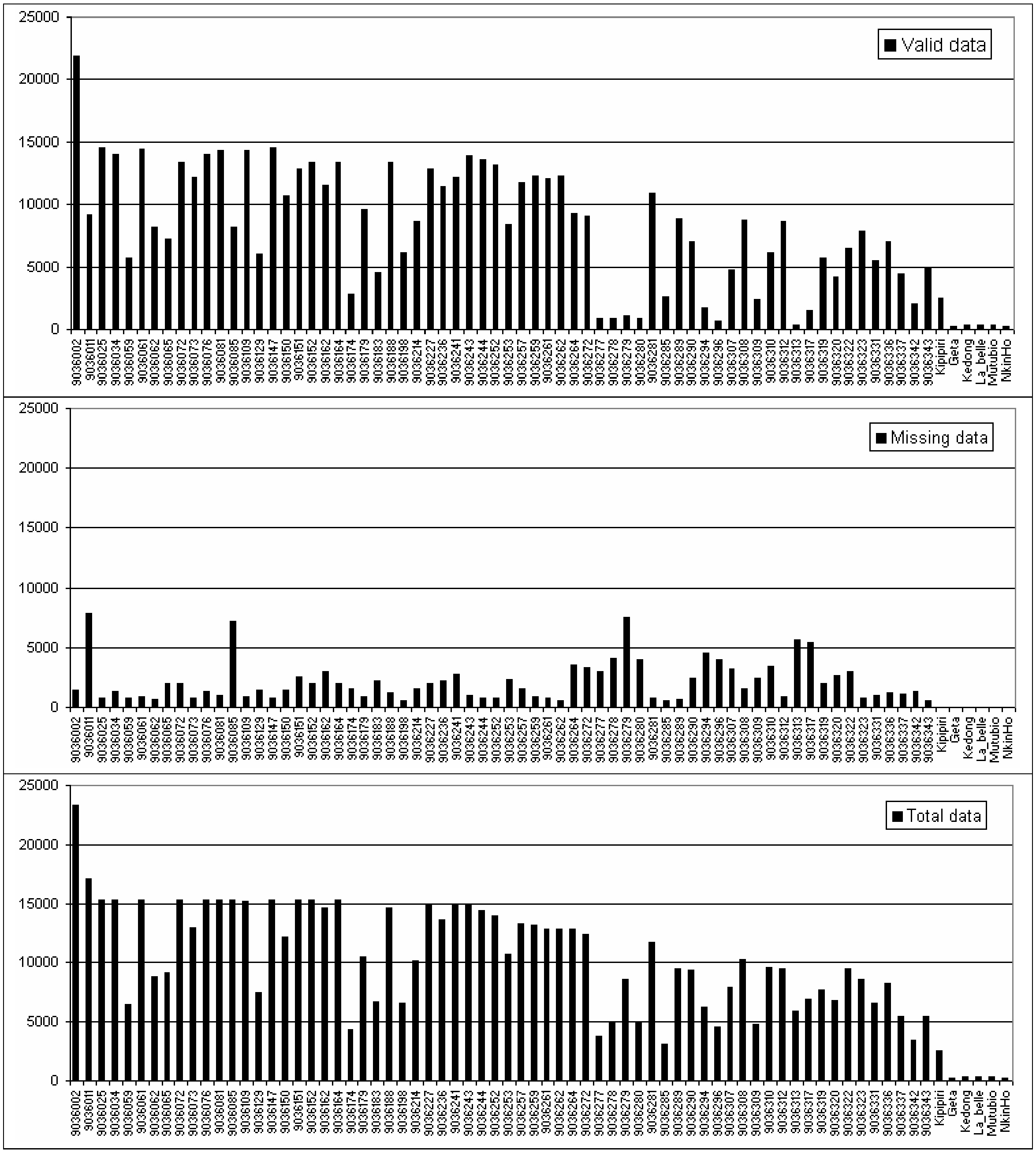


Figure 3-5: Status of daily rainfall record of 72 stations, Lake Naivasha basin (1926-2004).

Weather generator requires statistical parameters of rainfall as an input. Mean monthly rainfall and mean annual rainfall data were calculated using SPSS and EXCEL. After analysing monthly and annual rainfall data and annual rainfall data with respect to elevation of the stations in the study area, it was found that monthly rainfall has less correlation coefficient but annual rainfall has high correlation coefficient. It was not possible to do cokriging, as cross-correlation between monthly rainfall data and elevation was less. So, annual rainfall data was chosen for study purpose. Annual rainfall gave correlation coefficient = 0.5 with elevation. Scatter plot of mean annual rainfall and elevation is presented below:

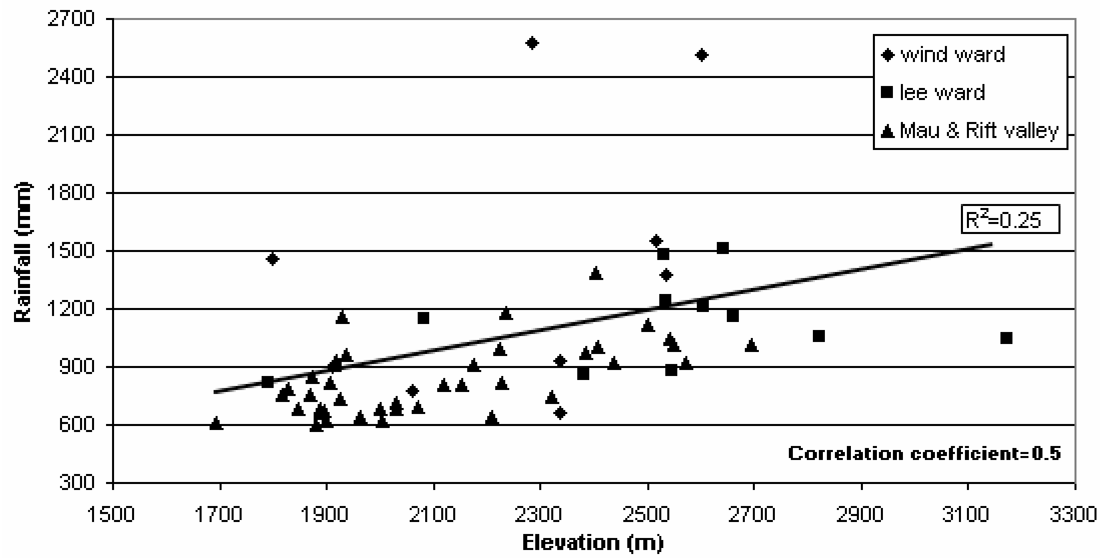


Figure 3-6: Scatter plot of mean annual rainfall and elevation.

4. Weather generator and optimization of its input parameters

4.1. Introduction

Synthetically generated sequences of daily precipitation are often used for investigating likely scenarios for agricultural water requirements, reservoir operation for analyses of antecedent moisture conditions, and runoff generation in a watershed (Lall et al., 1996).

Meteorological data are needed to evaluate the long-term effects of proposed, man-made hydrologic changes. These evaluations are often undertaken using deterministic mathematical models of hydrologic processes. The models require weather data as input. In addressing hydrologic responses to weather inputs it is seldom sufficient to examine only the response to observed weather events. Use of observed sequences gives a solution based on only one realization of the weather process. What would be the result if another series with the same properties as the observed series were used? What is the range of results that may be obtained with other equally likely weather sequences? To answer these questions, it is desirable to generate synthetic sequences of weather data based on the stochastic structure of the meteorologic processes.

The meterological variables needed for most hydrologic models include precipitation, maximum and minimum temperatures, solar radiation, or some related variable (Knisel, 1980). These variables are usually recorded daily, and most deterministic models require daily values. This study therefore is to develop a technique for simulating daily values of precipitation.

To develop a simulation model of the meterological variables of interest, one must develop a concept of the stochastic relationships that underlie the basic meteorogical processes. The processes are time dependent within each variable and interdependent among the four variables. Both radiation and temperature are more likely to be below normal on rainy days than on dry days. Similarly, maximum temperature will likely be low on a cloudy day with low solar radiation. Maximum and minimum temperatures on a given day will be related because of heat storage in the soil and surrounding atmosphere. Maximum temperature should be serially correlated because of heat storage from one day to the next. The processes exhibit seasonal oscillations for each variable. A model for simulation of daily weather variables should be able to account for these interrelations and seasonal variations. The general approach was to consider precipitation as the primary variable and then condition the other three variables for a given day on whether the day was wet or dry.

Many models have been proposed for simulating daily precipitation (Buishand, 1978; Chin, 1977; Gabriel and Newman, 1962). Since precipitation was chosen as the primary variable and daily precipitation amounts were determined independently of the other variables, any precipitation model that produces daily precipitation values (subject to some criterion of goodness) could be used for the precipitation component. A simple Markov chain exponential model was used for the precipitation component to illustrate the concept. A first-order Markov chain was used to describe the occurrence of wet or dry days (Bailey, 1964). On days with rain the exponential distribution was used to describe the amount of rain.

With a first-order Markov chain the probability of rain on a given day is conditioned on the wet or dry status of the previous day. The Markov chain model for daily precipitation occurrence has been studied extensively. (Gabriel and Newman, 1962) found that a first-order Markov chain provided a satisfactory model for daily precipitation occurrence at Tel Aviv, Israel. A Markov chain was also used by (Caskey, 1963), (Weiss, 1964), and (Hopkins and Robillard, 1964) to describe the occurrence of sequences of wet or dry days. (Haan et al., 1976) used a first-order Markov chain with six rainfall states to model both occurrence and amounts of precipitation. Smith and Schreiber (1973) found a first-order Markov chain to be superior to a Bernoulli model (sequential independence) for describing the occurrence of wet or dry days in south-eastern Arizona.

To simulate precipitation throughout the year, the seasonal nature of weather generator's input parameters may be described by using Fourier series or other periodic functions (Richardson, 1981).

Problems of quantifying rainfall variability in space with respect to climatic elements have been subject of numerous studies. Many studies applied a combination of time domain multivariate statistics such as harmonic analysis, Fourier analysis to determine relationships between and among the climate elements. A common and well-recognized shortcoming of such approaches has been the assumption that climate data is stationary and linear, a criterion few data sets from natural phenomena satisfy (Huang et al., 1998).

4.2. Weather generator (WXGEN) Model

Stochastic weather generators have been proposed as one technique for simulating time series consistent with the current climate as well as for producing scenarios of climate change (Wilks, 1992). In particular, such simulations have been used in assessments of the effects of climate variability and change, primarily on managed environmental systems (Mearns et al., 1997). Because of this recent attention, an awareness of the limitation of stochastic models is starting to develop (Johnson et al., 1996; Semenov et al., 1998).

The rainfall generator (WXGEN) is a first-order Markov chain model developed by (Nicks, 1974). A first-order Markov chain is used to define the day as wet or dry. When a wet day is generated, a skewed distribution is used to generate the precipitation amount. With the first-order Markov chain model. The probability of rain on a given day is conditioned on the wet or dry status of the previous day. A wet day is defined as a day with 0.1 mm of rain or more. Given the wet-dry probabilities, the model stochastically determines the occurrence of rainfall in a particular day. When a rainfall event occurs, the amount is determined by generation from a skewed normal daily rainfall distribution. The Markov chain model consists with two states, namely wet and dry days. Simulations require four transitional probabilities within and between states.

Day (i-1) \ Day (i)	Wet	Dry
Wet	P_i (W/W)	P_i (W/D)
Dry	P_i (D/W)	P_i (D/D)

Table 4-1: Different transition probabilities used in weather generator

P_i *(W/W)* – Probability of wet day on day *i* given a wet day on day *i*-1
P_i *(W/D)* – Probability of wet day on day *i* given a dry day on day *i*-1
P_i *(D/W)* – Probability of dry day on day *i* given a wet day on day *i*-1
P_i *(D/D)* – Probability of dry day on day *i* given a dry day on day *i*-1

Once first two transition probabilities are inserted into the model, program derives other two probabilities using following two relationships:

$$P_i(D/W) = 1 - P_i(W/W)$$

$$P_i(D/D) = 1 - P_i(W/D)$$

Where $P_i(D/W)$ is the probability of a dry day on day *i* given a wet day on *i-1* and $P_i(D/D)$ is the probability of a dry day on *i* given a dry day on day *i-1*.

To define a day as a wet or dry, the model generates a random number between 0.0 and 1.0. This random number is compared to the appropriate wet-dry probability, Pi(W/W) or Pi(W/D). If the random number is equal to or less than the wet-dry probability, the day is defined as wet. If the random number is greater than the wet-dry probability, the day is defined as dry.
Then the amount of precipitation on a wet day is calculated using following equation:

$$R_{day} = \mu_{day} + 2 \cdot \sigma_{day} \cdot \left\{ \frac{\left[\left(SND_{day} - \frac{g_{day}}{6} \right) \cdot \left(\frac{g_{day}}{6} \right) + 1 \right]^3 - 1}{g_{day}} \right\}$$

Where: R_{day} = amount of precipitation on a given day (mm)
μ_{day} = long term mean of daily precipitation (mm) for the day
σ_{day} = long term standard deviation of daily precipitation (mm) for the day
SDN_{day} = standard normal deviation calculated for the day
g_{day} = long term coefficient of skewness for daily precipitation in the day.

The long term mean daily precipitation (mm) for the day is calculated:

$$\mu_{day} = \frac{PCPMM}{PCPD}$$

Where:
PCPMM = average amount of precipitation falling in day (mm)
PCPD = average number of days of precipitation in day.

The standard normal deviate (SDN) for the day is calculated:

$$SDN_{day} = \cos(6.283 \cdot rnd_2) \cdot \sqrt{-2\ln(rnd_1)}$$

Where rnd_1 and rnd_2 are random number between 0.0 and 1.0.

The model generates rainfall using input based on existing historical rainfalls. It requires the long-term daily statistics such as mean rainfall, standard deviation and skewness. The model uses the same set of daily statistics for generating long time series of rainfall.

4.3. Optimization of WXGEN input parameters

4.3.1. Frequency, Trend and Fourier analysis of temporal WXGEN input parameters

In analysing aggregated WXGEN input parameters, moving averages are used to emphasize the direction of a trend and smoothed out the data or "noise" that are causing confusion in interpretation. 10 days moving averages are taken to smooth data series and it was possible to spot the trends.

Fourier series is used if the function is periodic, so that it repeats over and over again, then irrespective of the function's behaviour; the function may be expressed as a series of sine and cosine. A function *f(t)* is periodic if the function values repeat at regular intervals of the independent variable *t*. The regular interval is referred to as the period *(T)*.
Fourier transformation provides a powerful tool for the analysis of stationary processes because for such processes the Fourier components are uncorrelated. A Fourier polynomial is an expression of the form:

$$F_n(x) = a_0 + (a_1\cos(x) + b_1\sin(x)) + ... + (a_n\cos(nx) + b_n\sin(nx))$$

$$F_n(x) = a_0 + \sum_{k=1}^{k=n}(a_k\cos(kx) + b_k\sin(kx))$$

Where, a_0, a_i and b_i are constant for i = 1,……, n
The Fourier polynomials are 2π periodic function.

In the case study, Solver in EXCEL is used to get Fourier series of WXGEN input parameters (i.e. mean, standard deviation, skewness, wet-wet Markov chain probability, wet-dry Markov chain probability and average number of rainy days). The Fourier transform of the parameters time series obtained gives a rather large number of possible choices of attributes, i.e. amplitude and phase values to apply in qualitative interpretation. These graphs are presented below:

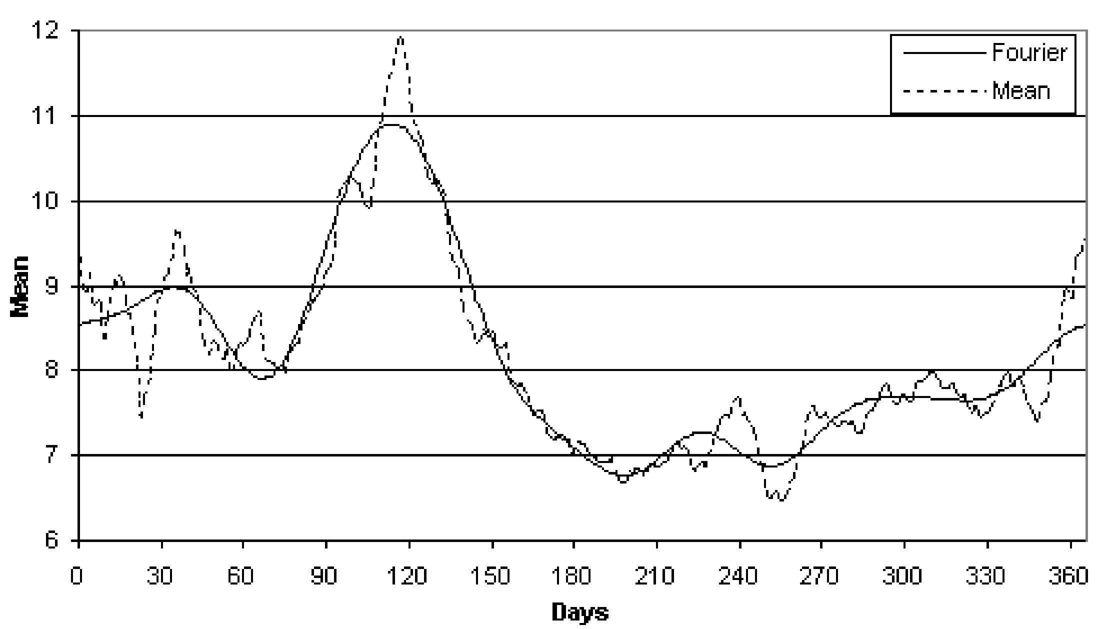


Figure 4-1: The temporal variability of the mean.

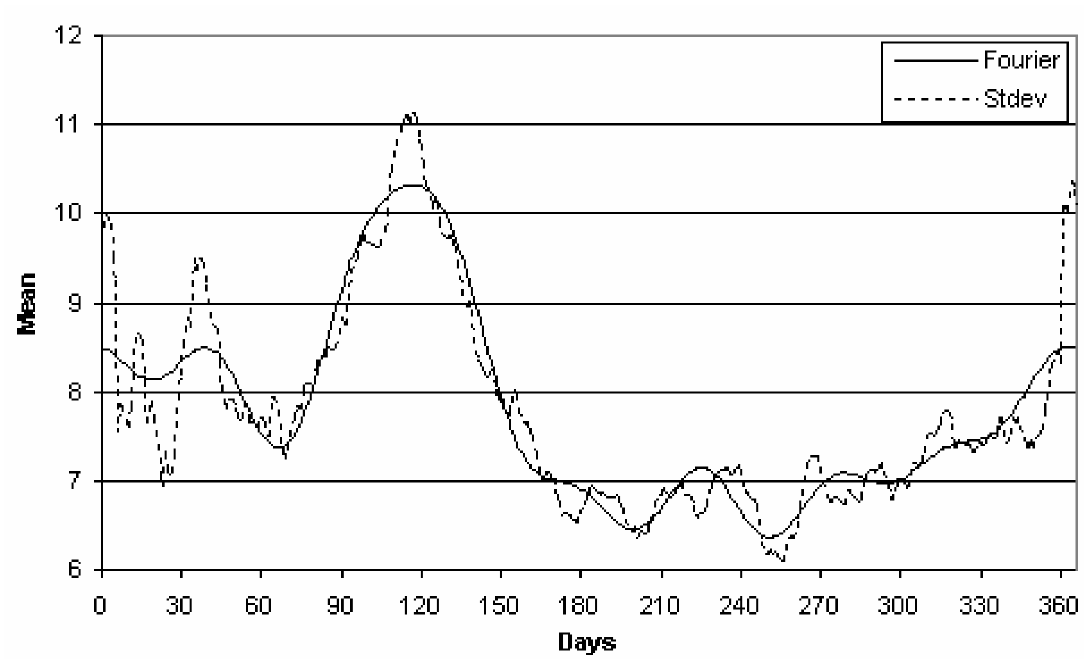


Figure 4-2: The temporal variability of the standard deviation.

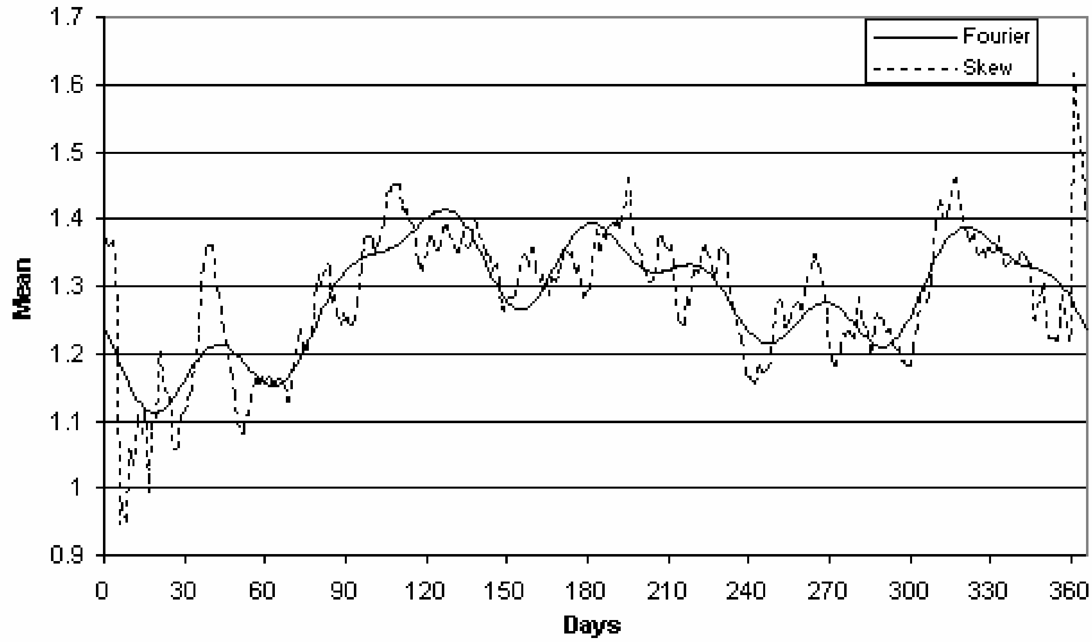


Figure 4-3: The temporal variability of the skewness.

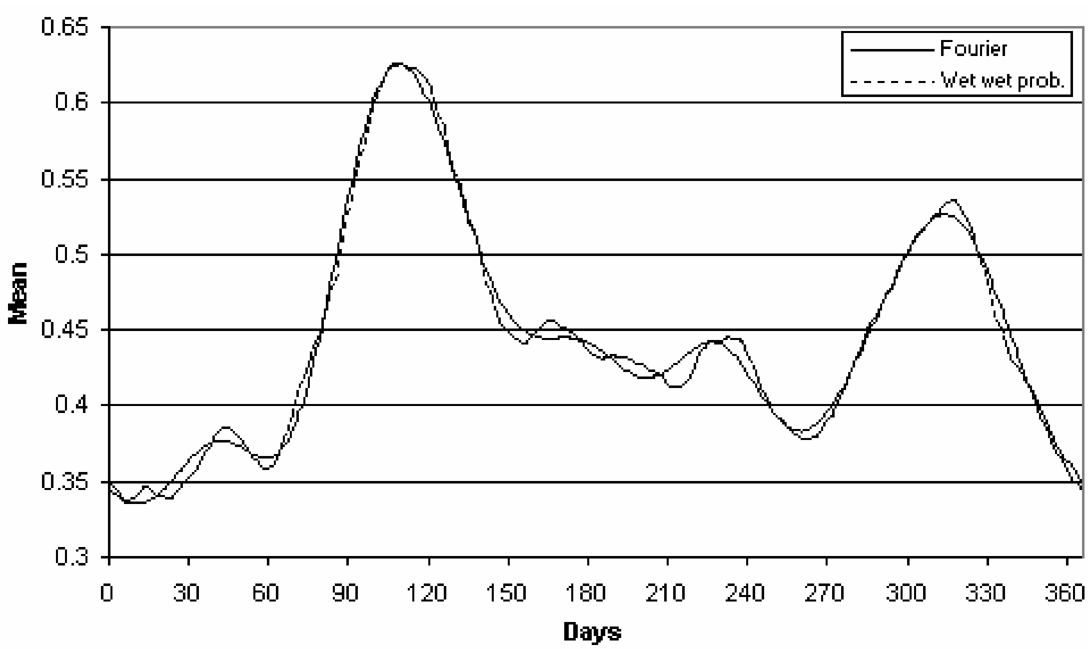


Figure 4-4: The temporal variability of the wet-wet probability.

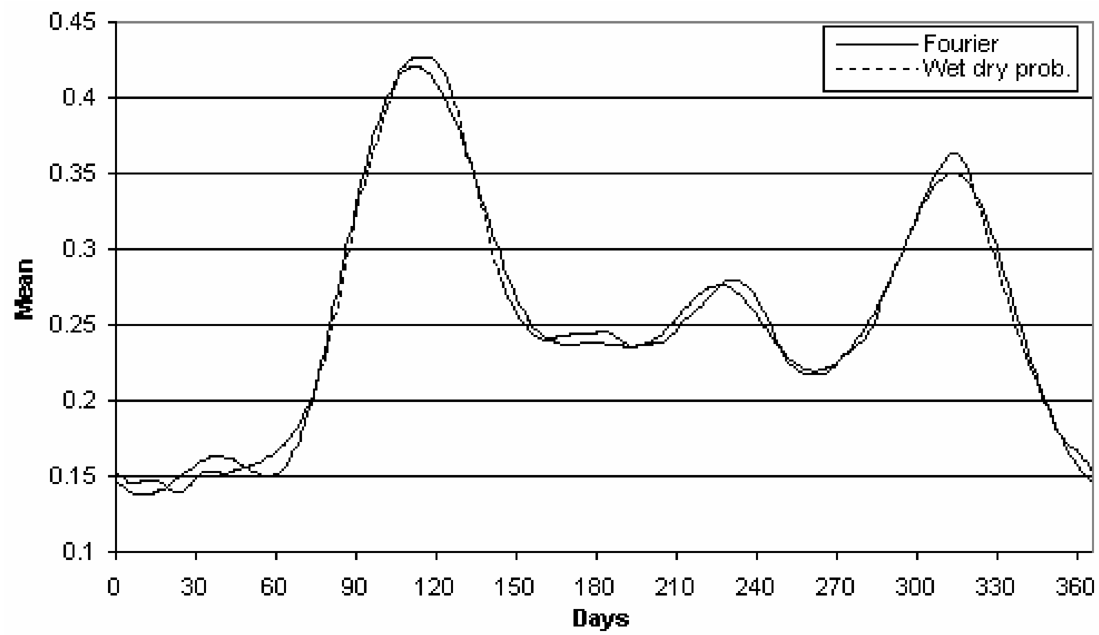


Figure 4-5: The temporal variability of the wet-dry probability.

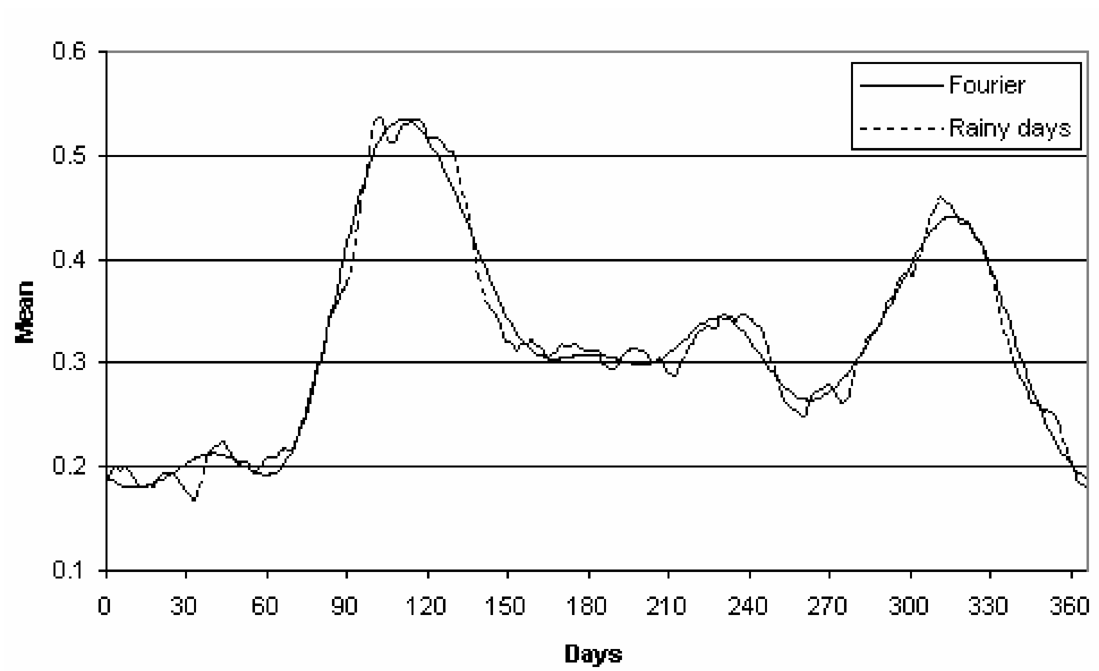


Figure 4-6: The temporal variability of the average number of rainy days.

4.4. Discussion of the result

In attempting to optimize the weather generator input parameters, it was observed that most of the parameters were having bimodal distribution except skewness (Figure 4-3). It could be because of its dependency on the mean and standard deviation. Other parameters were showing good results, as they match with bimodal temporal variability of rainfall distribution observed in Lake Naivasha basin on annual basis.

5. Co-kriging and Interpolation of the WXGEN input parameters

5.1. Introduction

Spatial studies focusing on environmental, ecological and agricultural phenomena require a proper and carefully designed strategy for collecting data. Data can be difficult or expensive to collect, and both the sampling design and the quantity of the data may affect the final qualities of an analysis (Cochran, 1977; Muller, 1998).

Measured rainfall data are important to many problems in hydrologic analysis and designs. For example, the ability of obtaining high resolution estimates of spatial variability in rainfall fields becomes important for identification of locally intense storms that could lead to floods and especially flash floods. The accurate estimation of the spatial distribution of rainfall requires a very dense network of instruments, which entails large installation and operational costs. Also, vandalism or the failure of the observer to make the necessary visit to the gage may result in even lower sampling density; thus, it is necessary to estimate point rainfall at unrecorded locations from values at surrounding sites.

Geostatistics is the set of statistical tools that offers a way of describing the spatial structure of many natural phenomena and provides adaptations of classical regression techniques to take advantage of this organization. Although these techniques were developed originally for geoscience applications, it has been applied to the mapping of precipitation fields. Geostatistical estimation techniques, called Kriging, provide unbiased linear estimations with minimum error variance. However, all Kriging methodologies need some spatial model (covariance, correlogram or variogram) providing the spatial continuity between original data that it is used to calculate the estimated values. Definition of a valid spatial continuity model from raw data is the main implementation problem of these techniques.
Geostatistics, which is based on the theory of regionalized variables (Goovaerts, 1997; Goovaerts, 1998a; Journel and Huijbregts, 1978), is increasingly preferred because it allows one to capitalize on the spatial correlation between neighbouring observations to predict attribute values at unsampled locations. Several authors (Phillips et al., 1992; Tabios and Salas, 1985) have shown that geostatistical prediction techniques (kriging or cokriging) provide better estimates of rainfall than conventional methods. More sophisticated approaches, like cokriging, have been used to incorporate elevation into the mapping of rainfall (Hevesi et al., 1992b; Hevesi et al., 1992a).

Cokriging will allow carrying out an optimum estimation taking more than one variable into account, i.e. taking advantage of the relations between the variables to improve the estimation. For instance, altitude is an important additional variable when estimating precipitation. When no additional variables are used, in addition to longitude and latitude, cokriging is equivalent to the classical kriging.

In the present case the technique is applied to spatially continuous and discretely sampled variables: variables can take values in any point in space, and each known value applies to a constant and very small area comparatively to the scale of the interpolation. The variables under consideration take continuous values rather than discrete or categorical ones.

The technique of cokriging is based on the statistical theory of random functions. A random function can be defined as a theoretical function which provides for each given space location the statistical distribution of values that may occur. This theoretical function is in fact unknown; to derive it, we can only rely on a set of observed values which constitute what will be called the realization of the random function in certain space locations. All calculations will aim at building the best possible image of this random function on the basis of all values observed.

The estimation of a value through cokriging involves the following steps:

- A characterization of the spatial relations (dependence) between observations
- The modelization of this dependence with the help of particular functions, known as simple and cross-variograms
- The utilization of these functions for the estimation of the variable studied over a given area.

5.2. Co-kriging interpolation of weather generator input parameters

Weather generator model (WXGEN) is explicitly used to generate time series of daily climatic data by maintaining the statistical properties of historical data. The weather generator requires statistical properties like mean, standard deviation, skewness, wet-dry and wet-wet Markov chain probability and average number of rainy days.

Using cokriging to interpolate WXGEN input parameters with elevation, we can generate spatially distributed values and using those spatially distributed parameters we can generate rainfall value using WXGEN model.

In the case study long term daily rainfall data for whole year is used to obtain mean, standard deviation and skewness, and daily rainfall data is used to obtain wet-wet Markov chain probability, wet-dry Markov chain probabilities and average number of rainy days of the rain gauges in and around the study area. Then cokriging interpolation is applied on these input parameters with elevation. They are presented below:

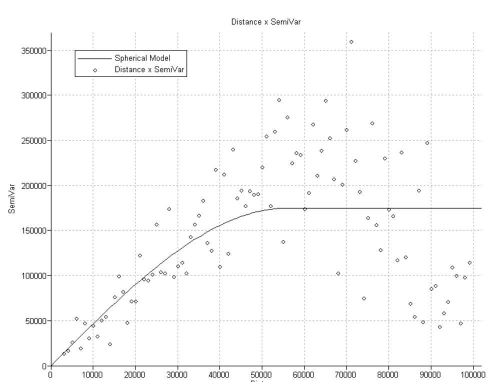


Figure 5-1: Semi-variogram model of elevation.

Spherical model		
Nugget	Sill	Range
50	175000	56000

Table 5-1: Parameters of fitted semi-variogram model of elevation.

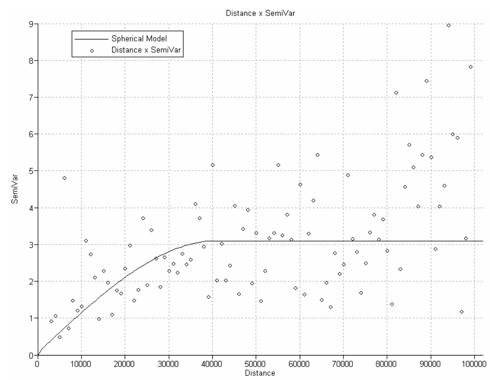


Figure 5-2: Semi-variogram model of mean daily rainfall.

Spherical model		
Nugget	Sill	Range
0.05	3.1	41000

Table 5-2: Parameters of fitted semi-variogram model of mean daily rainfall.

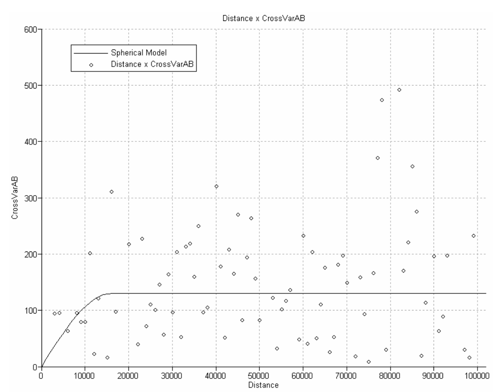


Figure 5-3: Cross-variogram model of mean annual rainfall and elevation.

Spherical model		
Nugget	Sill	Range
1.0	130	16000

Table 5-3: Parameters of fitted cross-variogram model of mean daily rainfall and elevation.

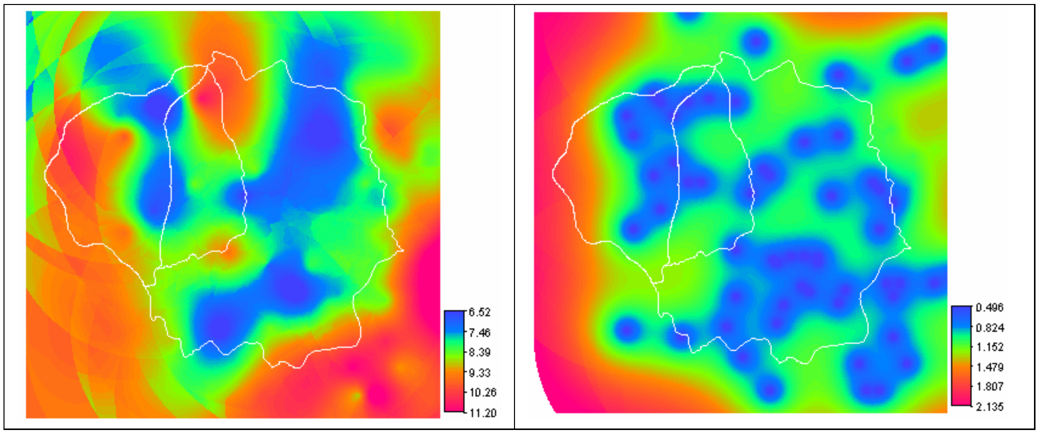


Figure 5-4: Cokriging predicted and Variance (error) maps of mean daily rainfall with elevation.

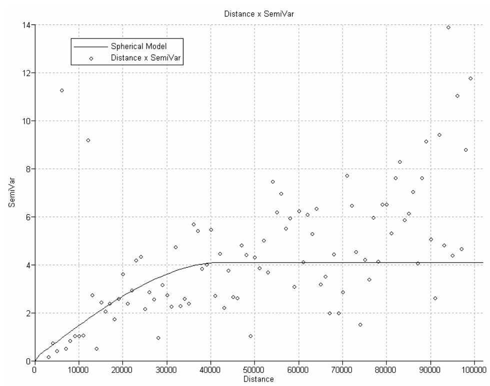


Figure 5-5: Semi-variogram model of standard deviation of daily rainfall.

Spherical model		
Nugget	Sill	Range
0.09	4.1	43000

Table 5-4: Parameters of fitted semi-variogram model of standard deviation of daily rainfall.

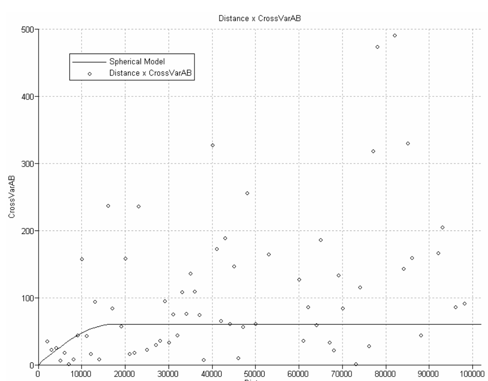


Figure 5-6: Cross-variogram model of standard deviation of daily rainfall and elevation.

Spherical model		
Nugget	Sill	Range
1.0	60	17000

Table 5-5: Parameters of fitted cross-variogram model of standard deviation of daily rainfall and elevation.

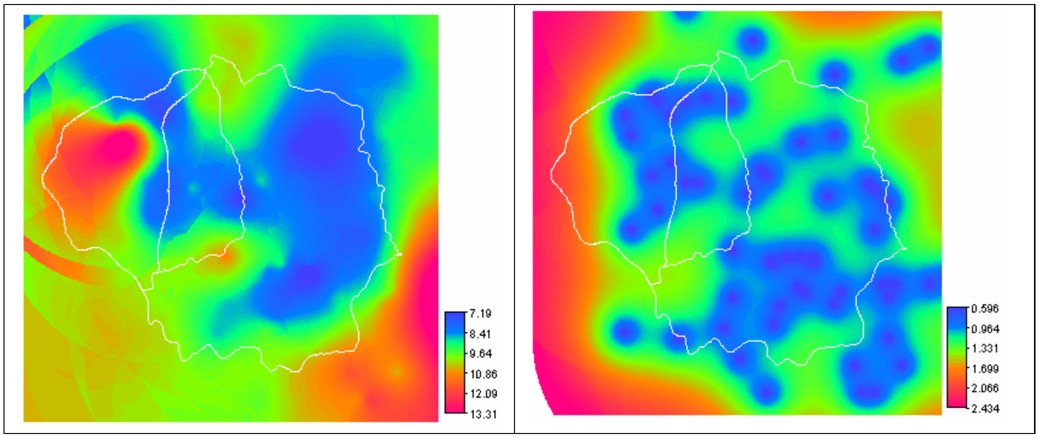


Figure 5-7: Cokriging predicted and Variance (error) maps of standard deviation of daily rainfall with elevation.

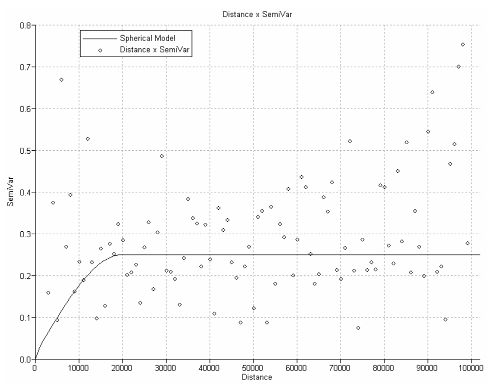


Figure 5-8: Semi-varigram model of skewness of daily rainfall.

Spherical model		
Nugget	Sill	Range
0.01	0.25	20000

Table 5-6: Parameters of fitted semi-variogram model of skewness of daily rainfall.

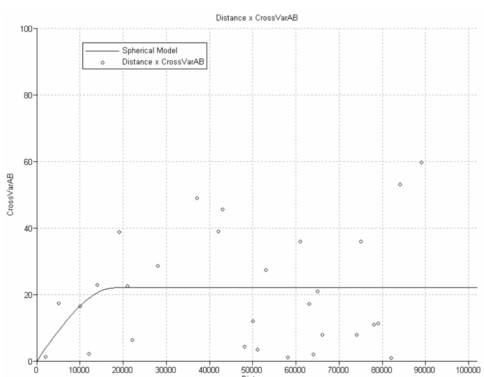


Figure 5-9: Cross-variogram model of skewness of daily rainfall and elevation.

Spherical model		
Nugget	Sill	Range
0.005	22	18000

Table 5-7: Parameters of fitted cross-variogram model of skewness of daily rainfall and elevation.

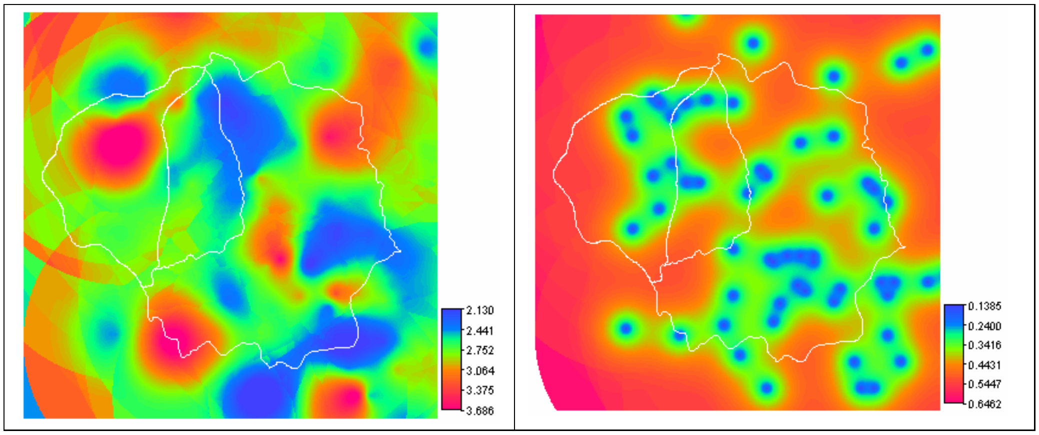


Figure 5-10: Cokriging predicted and Variance (error) maps of skewness of daily rainfall with elevation.

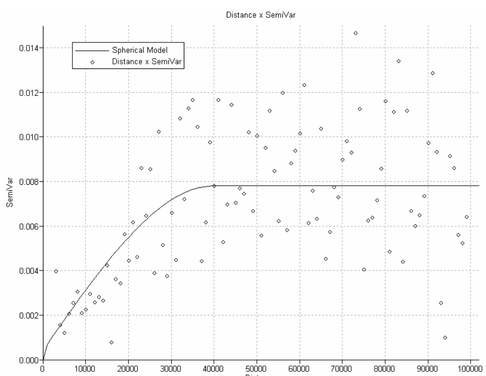


Figure 5-11: Semi-variogram model of wet-wet probability of daily rainfall.

Spherical model		
Nugget	Sill	Range
0.0004	0.0078	40000

Table 5-8: Parameters of fitted semi-variogram model of wet-wet probability of daily rainfall.

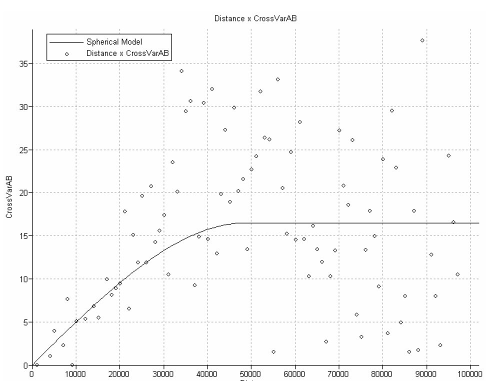


Figure 5-12: Cross-variogram model of wet-wet probability of daily rainfall and elevation.

Spherical model		
Nugget	Sill	Range
0.00005	16.5	49000

Table 5-9: Parameters of fitted cross-variogram model of wet-wet probability of daily rainfall and elevation.

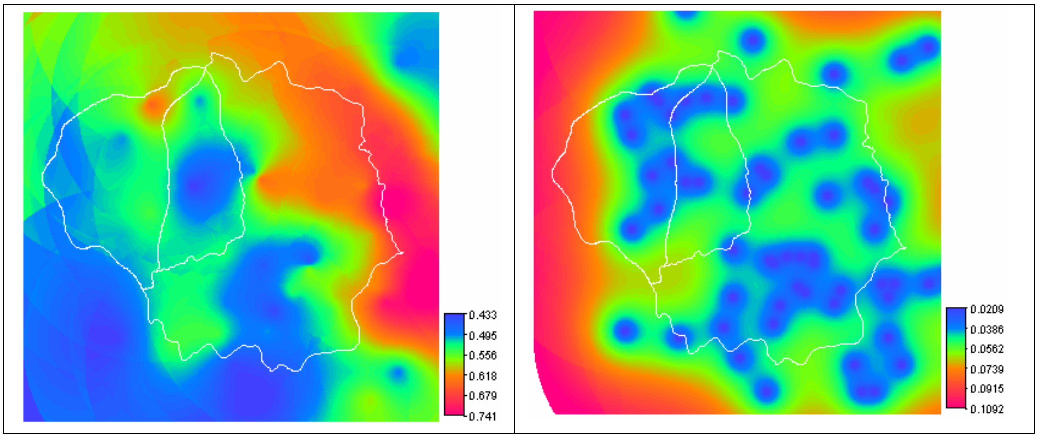


Figure 5-13: Cokriging predicted and Variance (error) maps of wet-wet probability of daily rainfall with elevation.

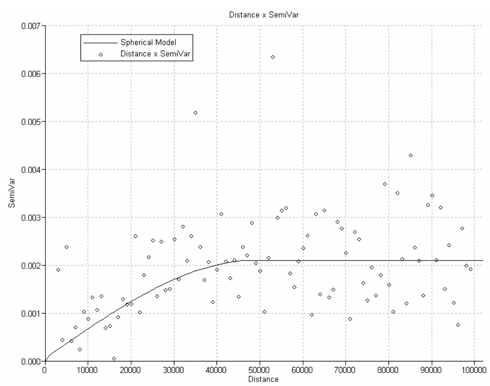


Figure 5-14: Semi-variogram model of wet-dry probability of daily rainfall.

Spherical model		
Nugget	Sill	Range
0.00005	0.0021	49000

Table 5-10: Parameters of fitted semi-variogram model of wet-dry probability of daily rainfall.

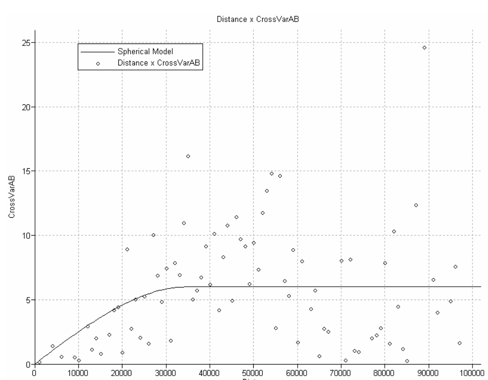


Figure 5-15: Cross-variogram model of wet-dry probability of daily rainfall and elevation.

Spherical model		
Nugget	Sill	Range
0.005	6	35000

Table 5-11: Parameters of fitted cross-variogram model of wet-dry probability of daily rainfall and elevation.

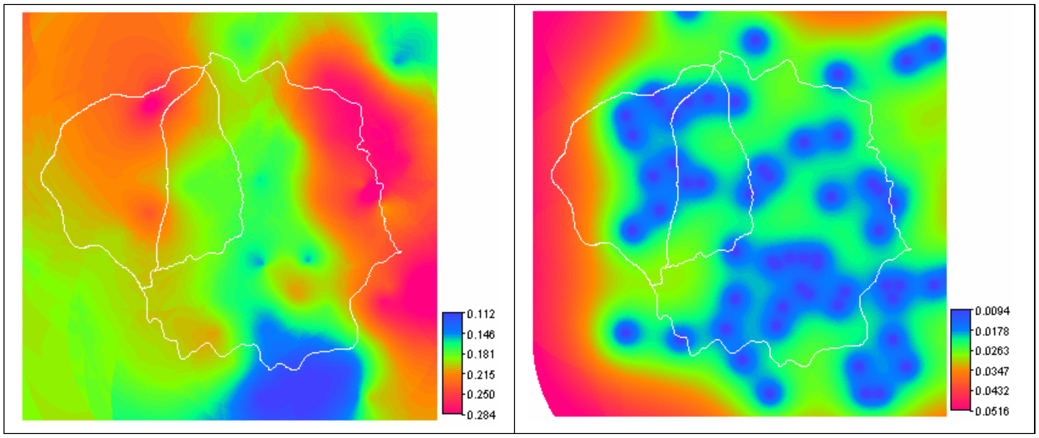


Figure 5-16: Cokriging predicted and Variance (error) maps of wet-dry probability of daily rainfall with elevation.

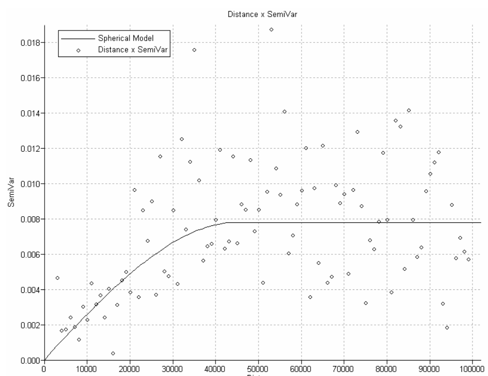


Figure 5-17: Semi-variogram model of number of rainy days of daily rainfall.

Spherical model		
Nugget	Sill	Range
0.00004	0.0078	45000

Table 5-12: Parameters of fitted semi-variogram model of number of rainy days of daily rainfall.

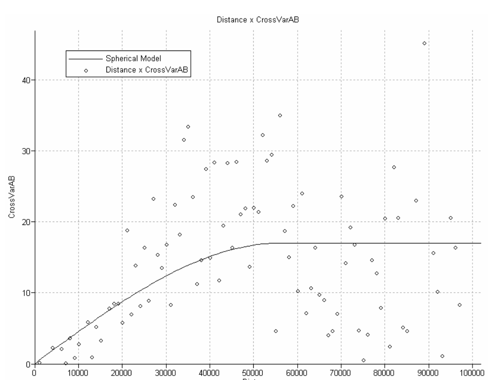


Figure 5-18: Cross-variogram model of number of rainy days of daily rainfall and elevation.

Spherical model		
Nugget	Sill	Range
0.005	17	56000

Table 5-13: Parameters of fitted cross-variogram model of number of rainy days of daily rainfall and elevation.

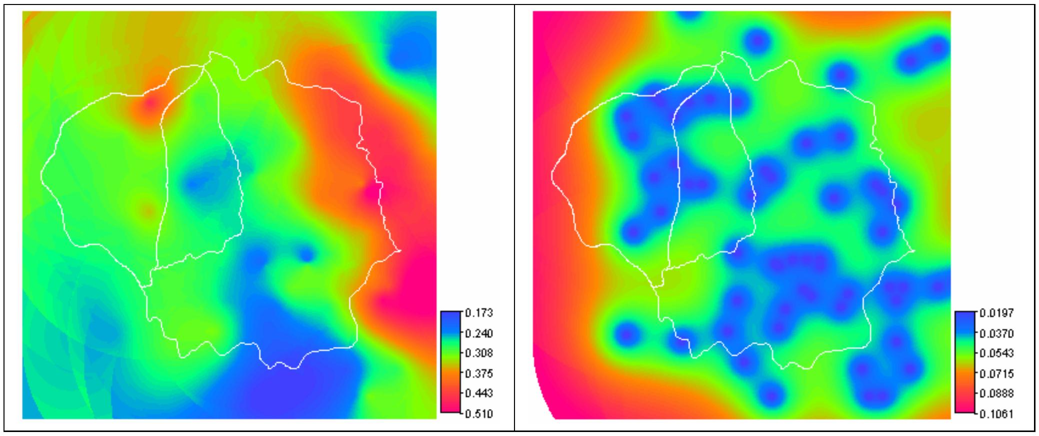


Figure 5-19: Cokriging predicted and Variance (error) maps of number of rainy days of daily rainfall with elevation.

5.3. Discussion of the result

In attempting to describe the cokriging interpolation of the weather generator input parameters, it was found that most of the cokriged maps are showing high value for the mountainous region and low value for the rift valley except skewness (Figure 5-10). Again, it could be because of its dependency on mean and standard deviation. Other parameters were showing good result, as they were showing spatial variability in rainfall with elevation observed in the Lake Naivasha basin.

Additional work has been done to compare cokriging with regression kriging. Mean annual rainfall data was taken to evaluate performance comparison of cokriging with regression kriging. In regression kriging, DEM was incorporated using linear equation (R = -105.53+0.42 E) and rainfall residual to get annual rainfall map (refer Appendix 7). In cokriging, point rainfall value was incorporated with elevation to get annual rainfall map (refer Figure 3-4). After comparing both maps, it was observed that cokriging performed better than regression kriging in predicting rainfall in the study area.

6. Results and Discussion

6.1. Introduction

As mentioned in the earlier chapters, the Geostatistic tool – Cokriging interpolation is applied to weather generator's input parameters to get spatially distributed map. Then those maps were used to generate spatially distributed synthetic daily rainfall. Weather generator model (WXGEN) is specifically developed to generate temporal synthetic daily rainfall. When applying WXGEN algorithm, it was necessary to fit the spatio-temporal characteristic of the rainfall. Using Fourier series approximation, it has been possible to integrate temporal characteristic of data.

6.2. Discussion of results

In attempting to access accurate spatial rainfall data in Lake Naivasha basin, Kenya, daily rainfall data was available. Monthly and annual rainfall data were aggregated for study purpose. Monthly rainfall data was discarded as it was showing less correlation with elevation. So, annual rainfall data was selected for the study purpose. Weather generator's input parameters like mean, standard deviation and skewness were obtained from annual rainfall and wet-wet Markov chain probability, wet-dry Markov chain probability and number of rainy days were obtained from daily rainfall for rain gages. Then they were interpolated using cokring with elevation. Obtained cokriged maps were enough to proceed for further work.

In the next step, long term daily rainfall data for wet period were aggregated and weather generator input parameters were obtained. Those data were harmonized using 10 days moving average and optimized using Fourier series approximation and were normalized. Normalized values were taken for further work.

In the final step, synthetic daily rainfall data were obtained using weather generator model (WXGEN).

In the case study, weather generator input parameters for Julian day 120 were taken. They are presented below:

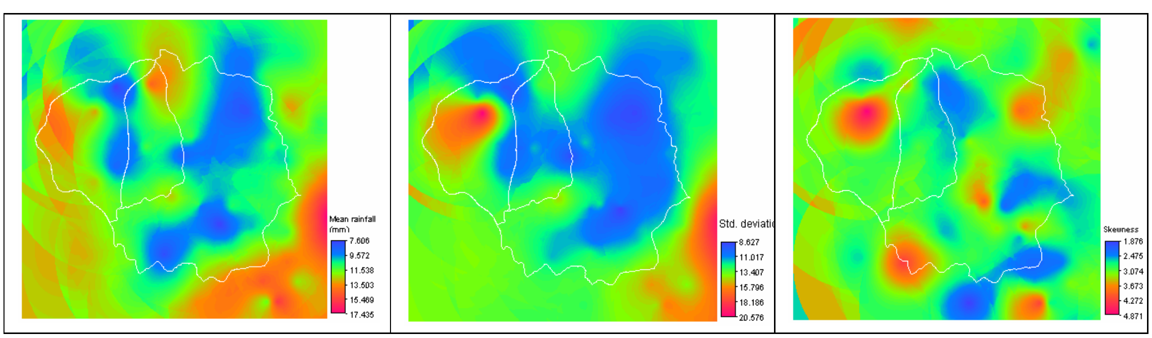


Figure 6-1: Spatio-temporal maps of weather generator input parameters for Julian day 120.

Finally, synthetic daily rainfall data for Julian day 120 were obtained using weather generator (WXGEN) model and is presented below:

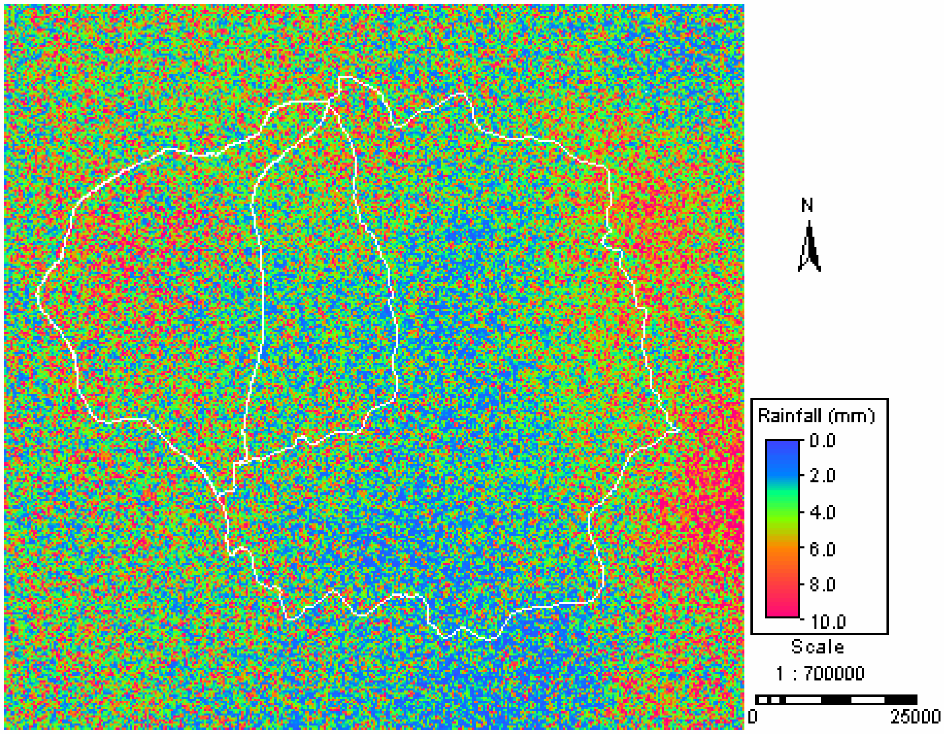


Figure 6-2: Synthetic rainfall map for julian day 120 generated using Weather generator model (WXGEN) model, Lake Naivasha basin.

The rainfall map obtained above shows high rainfall values on the mountains and low value on the rift valley. It is seen that the rainfall is not homogenous in the study area. Pixel values of rainfall should be improved with condition to measured daily data by fitting with the rainfall trend existing in the historic rainfall data.

There has been a limitation in generating rainfall data. Condition to define day as dry if the random number is greater than the wet-dry probability could not be accurately incorporated in the WXGEN algorithm. Also, continuous rainfall field could not be generated with weather generator model (WXGEN). Generally, it was hampered by the limitations of time representation in spatial data structures.

7. Conclusions and Recommendations

7.1. Conclusions

The general objective of this study was to extent the work on synthetic rainfall data to estimate the input parameters for weather generator spatially. The study was first concentrated on the preparation of basic data of input parameters of weather generator. The study was complimented by using SRTM DEM. Geostatistical technique (cokriging) supplemented the research study.

Main achievement of this study was to interpolate the weather generator input parameters (mean, standard deviation, skewness, wet-wet Markov chain probability, wet-dry Markov chain probability and average number of rainy days) using cokriging with elevation. In applying cokriging with elevation, it was necessary for rainfall data to have high correlation coefficient with elevation. It was found that monthly rainfall data showed less correlation and annual rainfall data showed good correlation coefficient (=0.5). So, annual rainfall data was selected for the study purpose.

Another achievement was to harmonize rainfall statistics for different time period. For this, 10 days moving average was applied to smooth out rainfall statistics and it was possible to spot trends in the data series. Then Fourier series approximation was applied to optimize already smoothed rainfall statistics.

Finally, spatio-temporal distributed map for the specific Julian day(s) were obtained using weather generator model.

The purpose of the stochastic weather generator is to produce rainfall data which are statistically similar to the observed rainfall series. In other words, the statistics (including means, variances, frequency of occurrence of extremes, correlations and lag-correlations between variables) derived from the synthetic data should be statistically insignificantly different from those derived from the observed data. Direct and indirect method can be used to validate the output. Direct method involves comparison of statistics of generated rainfall with observed rainfall. Indirect method involves running hydrological modelling like water balance model and others.

In this case study, for validation purpose station Naivasha Distric Office (station id 9036002) was selected, as it is having best quality daily rainfall record. Observed mean rainfall for Julian day 120 of this station is compared with the rainfall for Julian day 120 generated using weather generator model (WXGEN) for the same station location. They are presented below:

	Rainfall (mm)
Observed	3.6
Simulated	3.1

Table 7-1: Observed and simulated rainfall for Julian day 120 for station Naivasha D. O.

It was found that the difference (= 0.5 mm) between the observed and simulated rainfall for Julian day 120 is insignificant.

Thus it can be inferred that:

- Weather generator input parameters can be accurately spatially and temporally modelled
- Spatially correlated weather generator model address the problem of the variation of rainfall data.

7.2. Recommendations

Even though the combination of geostatistic technique (cokriging) with weather generator model addresses the problem of the spatio-temporal variability of rainfall data, time series for ‘every point in space’ observing the historic rainfall trends still remains question. It is essential to improve quality of data series in space.

Another possibility to answer the spatio-temporal variability of rainfall data is to use remotely sensed data such as METEOSAT or Meteosat Second Generation (MSG-1), as they observes all the precipitation clouds within its field of view in 15 minutes cycles.

REFERENCES

Bailey, N.T.J., 1964. The Elements of Stochastic Processes. John Wiley, New York, 39 pp.
Barrett, E.C. and Martin, D.W., 1981. The use of satellite data in rainfall monitoring. Remote sensing unit, Dapartment of Geography, University of Bristol, U.K.
Buishand, T.A., 1978. Some remarks on the use of daily rainfall models. J. Hydrol., 36: 295-308.
Caskey, J.E.J., 1963. A Markov chain model for the probability of precipitation occurrence in intervals of various lengths. Mon. Weather Rev., 91: 298-301.
Chin, E.H., 1977. Modeling daily precipitation occurrence process with Markov chain. Water Resources Research, 13(6): 949-956.
Cochran, W.G., 1977. Sampling Techniques. Wiley, New York.
Dingman, S.L., 2002. Physical Hydrology. Prentice Hall, New Jersey, 646 pp.
Eric, P.J.B., Beurs, K.M.d. and Hartkamp, A.D., 2001. Kriging and thin plate splines for mapping climate variables. International Journal of Applied Earth Observation and Geoinformation, 3(2): 204.
Gabriel, R. and Newman, J., 1962. A Markov chain model for daily rainfall occurrence at Tel Aviv, Israel. Q. J. R. Meterol. Soc., 88: 90-95.
Goovaerts, P., 1997. Geostatistics for Natural Resources Evaluation. Oxford University Press, New York.
Goovaerts, P., 1998a. Geostatistical tools for characterizing the spatial variability of microbiological and physico-chemical soil properties. Biol. Fertil. Soils, 27(4): 315-334.
Grimes, D.I.F. and Bonafico, R., 1998. Drought and flood warning in Southern Africa. Thomas Telford Publishing, 1 Heron Quay, London, UK, 213 pp.
Haan, C.T., Allen, D.M. and Street, J.O., 1976. A Markov chain model of daily rainfall. Water Resources Research, 12(3): 443-449.
Hevesi, J.A., Flint, A.L. and Istok, J.D., 1992b. Precipitation estimation in mountainous terrain using multivariate geostatistics. Part II: Isohyetal maps. J. Appl. Meteor., 31: 677-688.
Hevesi, J.A., Istok, J.D. and Flint, A.L., 1992a. Precipitation estimation in mountainous terrain using multivariate geostatistics. Part I: Structural analysis. J. Appl. Meteor., 31: 661-676.
Hopkins, J.W. and Robillard, P., 1964. Some statistics of daily rainfall occurrence for the Canadian prairie provinces. J. Appl. Meteorol., 3: 600-602.
Huang, N. et al., 1998. The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis. Proceedings of the Royal Society of London, 454: 903-995.
Isaaks, E.H. and Srivastava, R.M., 1989. An Introduction to Applied Geostatistics. Oxford University Press, New York, 561 pp.
Johnson, G.L., Hanson, C.L., Hardegree, S.P. and Ballard, E.B., 1996. Stochastic weather simulation: Overview and analysis of two commonly used models. J. Appl. Meteor., 35: 1878-1896.
Journel, A.G. and Huijbregts, C.H., 1978. Mining Geostatistics. Academic Press, London.
Knisel, W.G., 1980. CREAMS: A field scale model for chemicals, runoff, and erosion from agricultural management systems. Conserv. Res. Rep., 26. U.S. Dep. of Agricultural, Washington D.C., 640 pp.
Lall, U., Rajagopalan, B. and Tarboton, D.G., 1996. A nonparametric wet/dry spell model for resampling daily precipitation. Water Resources Research, 32(9): 2803-2823.
Lang, C., 2001. Kriging Interpolation, Cornell University, Ithaca, New York.
Mearns, L.O., Rosenzweig, C. and Goldberg, R., 1997. Mean and variance change in climate scenarios: Methods, agricultural applications, and measures of uncertainty. Climate Change, 35: 367-396.

Muller, W.G., 1998. Collecting Spatial Data - Optimum Design of Experiments for Random Fields. Physical - Verlag, Heidelberg.
Muthuwatta, L.P., 2004. Long term rainfall-runoff-lake level modelling of the Lake Naivasha basin, Kenya. MSc. Thesis, International Institute for Geo-information Science and Earth Observation, ITC, Enschede, The Nethaerlands, 71 pp.
Nicks, A.D., 1974. Stochastic generation of the occurrence, pattern and location of maximum amount of daily rainfall. In Proc. Symp. Statistical Hydrology, Aug.-Sept. 1971, Tuscon, AZ, U.S. Department of Agriculture: 154-171.
Odeh, I.O.A., McBratney, A.B. and Chittleborough, 1995. Further results on prediction of soil properties from terrain attributes: heterotopic cokriging and regression-kriging. Geoderma 67: 215-226.
Phillips, D.L., Dolph, J. and Marks, D., 1992. A comparison of geostatistical procedures for spatial analysis of precipitation in mountainous terrain. Agricultural and Forest Meteorology, 58: 119-141.
Rabus, B., Eineder, M., Roth, A. and Bamler, R., 2003. The shuttle radar topography mission--a new class of digital elevation models acquired by spaceborne radar. ISPRS Journal of Photogrammetry and Remote Sensing, 57(4): 241-262.
Richardson, C.W., 1981. Stochastic Simulation of Daily Precipitation, Temperature, and Solar Radiation. Water Resources Research, 17(1): 182-190.
Rodda, J.C., 1971. The precipitation measurement paradox-the instrument accuracy problem, Report on WMO/IHD projects no. 16, WMO No. 316.
Semenov, M.A., Brooks, R.J., Barrow, E.M. and Richardson, C.W., 1998. Comparison of the WGEN and LARS-WG stochastic weather generators for diverse climates. Climate Res., 10: 95-107.
Tabios, G.Q. and Salas, J.D., 1985. A comparative analysis of techniques for spatial interpolation of precipitation. Water Resources Bulletin, 21(3): 365-380.
Tessema, M.A., 2001. Estimation of rainfall using METEOSAT TIR data for the Naivasha catchment. MSc. Thesis Thesis, International Institute for Aerospace Survey and Earth Sciences, Enschede, The Netherlands., 79 pp.
Weiss, L.L., 1964. Sequence of wet and dry days described by a Markov chain probability model. Mon. Weather Rev., 92: 169-176.
Wilks, D.S., 1992. Adapting stochastic weather generation algorithms for climate change studies. Climatic Change, 22: 67-84.
Woodley, W.L., Olsen, A., Herndon, A. and Wiggert, V., 1974. Optimizing the Measurement of convective Rainfall in Florida. 99.

APPENDICES

Appendix 1: Station names and Locations.

	St_Id	St_Name	X cord. (m)	Y cord. (m)	Elev. (m)	Period	Year
1	9036002	Naivasha D. O.	215437.2	9919909.6	1962	1935-1998	64
2	9036011	Kedong Valley, Maai Mahiu	232895.8	9891229.7	1869	1926-1972	47
3	9036025	N. Kinangop Forest Station	236579.1	9935478.3	2661	1957-1998	42
4	9036034	Gilgil Railway Station	201658.3	9945330.7	2005	1957-1998	42
5	9036059	Kangari Farm, Naivasha	219876.6	9928092.2	2209	1957-1974	18
6	9036061	Kirita Forest Station	236604.1	9891232.3	2403	1957-1998	42
7	9036062	Naivasha Kongoni Farm	195030.7	9908737.5	2002	1967-1991	25
8	9036065	Naivasha Nanga Gerri	225452.3	9915185.3	2383	1957-1981	25
9	9036072	Mweiga Estate	268129.7	9961292.3	1912	1957-1998	42
10	9036073	Naivasha K.C.C. Ltd.	208739.3	9926239.0	1899	1957-1992	36
11	9036076	Technology Farm, Nakuru	167881.0	9966798.7	1913	1957-1998	42
12	9036081	Naivasha Vet. Expt. Station	212458.6	9928088.5	1925	1957-1998	42
13	9036085	Karameno Shopping Centr, N/Moru	251422.5	9985256.4	2060	1957-1998	42
14	9036109	Naivasha Marula Estate	207669.4	9927124.8	1890	1957-1998	42
15	9036129	Chokerereia F.C. Society	205018.6	9952060.1	2230	1957-1977	21
16	9036147	Elementaita, Soysambu Estate	188310.0	9948358.3	1819	1957-1998	42
17	9036150	Gilgil Kikopey Ranch	184600.1	9948356.8	1846	1957-1990	34
18	9036151	Subukia Pyrethrum Nursery	184589.7	9996315.2	2083	1957-1998	42
19	9036152	S. Kinangop Njabini F.T.C.	238445.7	9920723.3	2535	1957-1998	42
20	9036162	Kijabe Railway Station	231031.0	9898595.6	2119	1957-1996	40
21	9036164	S. Kinangop Forest Station	242154.1	9920725.2	2531	1957-1998	47
22	9036174	Aberdare Park Fort Jerusalem	240295.8	9942846.7	3173	1967-1978	12
23	9036179	Naivasha Korongo Farm	197605.7	9917016.2	1888	1957-1985	29
24	9036183	Naivasha Karati Scheme	227310.1	9918881.1	2546	1957-1975	19
25	9036188	Kinangop Sasumua Dam	240307.4	9917040.8	2517	1957-1996	44
26	9036198	New Gakoe Farm (Nakuru)	184593.1	9970488.0	1936	1957-1975	19
27	9036214	Naivasha Longonot Farm	208749.2	9909643.5	1897	1957-1984	28
28	9036227	Elementaita Nderit Ranger Post	180876.8	9953888.3	1828	1957-1997	41
29	9036236	Nakuru Lanet Police Post	180698.6	9966605.4	1873	1957-1994	38
30	9036241	Geta Forest Station	234725.4	9948375.4	2605	1958-1998	41
31	9036243	Dundori Forest Station	190291.0	9971381.6	2237	1958-1998	46
32	9036244	Kieni Forest Station	240313.7	9905979.6	2536	1958-1997	40
33	9036252	Menengai Forest Station	175300.5	9972334.0	2226	1960-1998	42
34	9036253	Thome Farmers No. 2	197598.3	9929928.5	2385	1960-1989	30
35	9036257	Eastern Rift Saw Mill Ltd.	244026.4	9898604.1	2336	1962-1998	37
36	9036259	Gatare Forest Station	251441.2	9920729.8	2602	1963-1998	36
37	9036261	Nakuru Meteorological Station	177161.6	9970486.3	1919	1964-1998	35
38	9036262	Olaragwai Farm Naivasha	216167.7	9928090.4	2070	1964-1998	35
39	9036264	N. Kinangop Mawingo Scheme	223589.3	9944687.8	2407	1964-1998	35
40	9036272	Mutubia Gate (A.N. Park)	236574.8	9946539.8	2643	1965-1998	34
41	9036277	Magura River	244002.9	9946542.4	3009	1966-1985	20
42	9036278	Riunge Hill	245859.8	9955756.7	3167	1967-1985	19
43	9036279	Culvert Camp	251427.4	9957605.3	2619	1968-1991	33
44	9036280	Chania River Aberd. Nat. Park	245861.5	9950226.3	2990	1969-1985	17
45	9036281	Naivasha W.D.D.	217537.8	9918237.8	2031	1965-1998	34

46	9036285	Longonot Akira Ranch	206913.5	9891210.1	1694	1967-1975	9
47	9036289	Wanjohi Chief's Camp	225432.9	9961281.9	2438	1969-1994	26
48	9036290	Malewa Farmer Coop. Soc.	216155.3	9959431.9	2323	1969-1994	26
49	9036294	Ngecha New Farmers Coop.	206879.6	9950213.1	2154	1969-1986	18
50	9036296	Kurase Hill Aberdare Park	240289.6	9963133.0	3347	1970-1985	16
51	9036307	Kangui Secondary School	203150.5	9987088.3	2542	1971-1992	22
52	9036308	Ngethu Water Supply	266295.5	9898617.8	1798	1971-1998	28
53	9036309	Miti Mingi Farm	177172.0	9940983.7	1908	1972-1985	14
54	9036310	Kamirithu Fancy Farm	169732.3	9961265.8	1929	1972-1998	27
55	9036312	Chamata Gate	225429.5	9977875.4	2822	1973-1998	26
56	9036313	Chebuswa Hill	232858.9	9974192.9	3229	1973.1989	17
57	9036317	Sakutiek C.C. Outpost	182763.8	9905940.9	2695	1973-1992	20
58	9036319	Mugunda Primary School	243994.9	9981561.4	2337	1974-1994	21
59	9036320	Naishi Ranger's Post	175307.3	9950201.1	1790	1979-1997	19
60	9036322	Crescent Island	210520.0	9914764.8	1881	1973-1998	26
61	9036323	Kianganye Farm Ichichi	257007.9	9922579.5	2286	1975-1998	24
62	9036331	Olchoro Agri. Office	167911.4	9907777.9	2571	1980-1997	18
63	9036336	Tumaini N.Y.S. Camp	197583.1	9970491.0	2499	1981-2003	23
64	9036337	Sururu Forest Station	169743.2	9935446.7	2551	1984-1998	15
65	9036342	Ndunyu Njeru	219877.5	9926244.8	2177	1984-1993	10
66	9036343	Olkaria Geothermal Station	199477.2	9900420.8	2031	1984-1998	15
67	Kipipiri	Kipipiri	219866.6	9952065.2	2303	1997-2004	8
68	Geta	Geta	222500.0	9958889.0	2513	1999-1999	1
69	Kedong	Kedong	215555.6	9903889.0	2111	2000-2001	2
70	La_belle	La belle	214194.1	9921152.8	1897	2001-2002	2
71	Mutubio	Mutubio	238888.9	9945278.0	3129	2002-2003	2
72	NKinHos	N. Kinangop Cath. Hospital	229027.8	9940556.0	2458	2000-2000	1

Appendix 2: Status of existing daily rainfall record (1926-2004).

			Number of data		
	St. id	**St. name**	**Valid**	**Missing**	**Total**
1	9036002	Naivasha D. O.	21901	1475	23376
2	9036011	Kedong Valley, Maai Mahiu	9211	7895	17106
3	9036025	N. Kinangop Forest Station	14573	767	15340
4	9036034	Gilgil Railway Station	14053	1287	15340
5	9036059	Kangari Farm, Naivasha	5752	730	6482
6	9036061	Kirita Forest Station	14458	882	15340
7	9036062	Naivasha Kongoni Farm	8183	673	8856
8	9036065	Naivasha Nanga Gerri	7180	1951	9131
9	9036072	Mweiga Estate	13379	1961	15340
10	9036073	Naivasha K.C.C. Ltd.	12138	827	12965
11	9036076	Technology Farm, Nakuru	14026	1314	15340
12	9036081	Naivasha Vet. Expt. Station	14358	982	15340
13	9036085	Karameno Shopping Centr, N/Moru	8146	7194	15340
14	9036109	Naivasha Marula Estate	14293	925	15218
15	9036129	Chokerereia F.C. Society	6019	1406	7425
16	9036147	Elementaita, Soysambu Estate	14574	766	15340
17	9036150	Gilgil Kikopey Ranch	10700	1443	12143
18	9036151	Subukia Pyrethrum Nursery	12804	2536	15340
19	9036152	S. Kinangop Njabini F.T.C.	13384	1956	15340
20	9036162	Kijabe Railway Station	11558	3021	14579
21	9036164	S. Kinangop Forest Station	13350	1990	15340
22	9036174	Aberdare Park Fort Jerusalem	2822	1561	4383
23	9036179	Naivasha Korongo Farm	9585	915	10500
24	9036183	Naivasha Karati Scheme	4531	2163	6694
25	9036188	Kinangop Sasumua Dam	13381	1229	14610
26	9036198	New Gakoe Farm (Nakuru)	6130	503	6633
27	9036214	Naivasha Longonot Farm	8639	1557	10196
28	9036227	Elementaita Nderit Ranger Post	12807	2015	14822
29	9036236	Nakuru Lanet Police Post	11434	2231	13665
30	9036241	Geta Forest Station	12135	2809	14944
31	9036243	Dundori Forest Station	13926	990	14916
32	9036244	Kieni Forest Station	13607	761	14368
33	9036252	Menengai Forest Station	13107	803	13910
34	9036253	Thome Farmers No. 2	8361	2353	10714
35	9036257	Eastern Rift Saw Mill Ltd.	11713	1528	13241
36	9036259	Gatare Forest Station	12253	896	13149
37	9036261	Nakuru Meteorological Station	12046	738	12784
38	9036262	Olaragwai Farm Naivasha	12259	525	12784
39	9036264	N. Kinangop Mawingo Scheme	9278	3506	12784
40	9036272	Mutubia Gate (A.N. Park)	9060	3358	12418

41	9036277	Magura River	811	2932	3743
42	9036278	Riunge Hill	873	4088	4961
43	9036279	Culvert Camp	1058	7556	8614
44	9036280	Chania River Aberd. Nat. Park	840	4028	4868
45	9036281	Naivasha W.D.D.	10893	826	11719
46	9036285	Longonot Akira Ranch	2586	548	3134
47	9036289	Wanjohi Chief's Camp	8882	614	9496
48	9036290	Malewa Farmer Coop. Soc.	6961	2413	9374
49	9036294	Ngecha New Farmers Coop.	1735	4505	6240
50	9036296	Kurase Hill Aberdare Park	624	3971	4595
51	9036307	Kangui Secondary School	4713	3231	7944
52	9036308	Ngethu Water Supply	8698	1529	10227
53	9036309	Miti Mingi Farm	2363	2445	4808
54	9036310	Kamirithu Fancy Farm	6169	3449	9618
55	9036312	Chamata Gate	8610	886	9496
56	9036313	Chebuswa Hill	329	5606	5935
57	9036317	Sakutiek C.C. Outpost	1514	5396	6910
58	9036319	Mugunda Primary School	5721	1949	7670
59	9036320	Naishi Ranger's Post	4199	2619	6818
60	9036322	Crescent Island	6510	2986	9496
61	9036323	Kianganye Farm Ichichi	7831	782	8613
62	9036331	Olchoro Agri. Office	5543	1032	6575
63	9036336	Tumaini N.Y.S. Camp	6998	1220	8218
64	9036337	Sururu Forest Station	4415	1064	5479
65	9036342	Ndunyu Njeru	2065	1343	3408
66	9036343	Olkaria Geothermal Station	4839	579	5418
67	Kipipiri	Kipipiri	2517	0	2517
68	Geta	Geta	214	0	214
69	Kedong	Kedong	354	0	354
70	La_belle	La belle	352	0	352
71	Mutubio	Mutubio	348	0	348
72	NKinHos	N. Kinangop Cath. Hospital	220	1	221
		Total	570899	140020	710919

Appendix 3: Weather Generator Statistics and Probability Value.

	St_Id	St_Name	X cord. (m)	Y cord. (m)	Elev. (m)	Pwd	Pww	Mean	std	skew	Rainy
1	9036002	Naivasha D. O.	215437.2	9919909.6	1962	0.21	0.54	5.67	7.51	2.94	0.31
2	9036011	Kedong Valley, Maai Mahiu	232895.8	9891229.7	1869	0.14	0.56	8.57	10.79	4.07	0.24
3	9036025	N. Kinangop Forest Station	236579.1	9935478.3	2661	0.24	0.60	8.66	7.80	2.24	0.37
4	9036034	Gilgil Railway Station	201658.3	9945330.7	2005	0.18	0.53	6.30	6.78	2.38	0.27
5	9036059	Kangari Farm, Naivasha	219876.6	9928092.2	2209	0.15	0.45	8.16	8.37	2.11	0.22
6	9036061	Kirita Forest Station	236604.1	9891232.3	2403	0.20	0.58	12.09	12.34	2.42	0.32
7	9036062	Naivasha Kongoni Farm	195030.7	9908737.5	2002	0.21	0.55	5.97	8.67	3.08	0.32
8	9036065	Naivasha Nanga Gerri	225452.3	9915185.3	2383	0.18	0.54	8.48	8.67	2.28	0.28
9	9036072	Mweiga Estate	268129.7	9961292.3	1912	0.21	0.47	8.94	9.77	3.25	0.28
10	9036073	Naivasha K.C.C. Ltd.	208739.3	9926239.0	1899	0.19	0.47	6.61	8.14	2.82	0.26
11	9036076	Technology Farm, Nakuru	167881.0	9966798.7	1913	0.23	0.55	7.57	8.50	2.78	0.34
12	9036081	Naivasha Vet. Expt. Station	212458.6	9928088.5	1925	0.19	0.49	7.44	9.37	3.82	0.27
13	9036085	Karameno Shopping Centr, N/Moru	251422.5	9985256.4	2060	0.16	0.50	8.74	9.53	2.32	0.24
14	9036109	Naivasha Marula Estate	207669.4	9927124.8	1890	0.15	0.46	8.69	9.22	3.08	0.22
15	9036129	Chokerereia F.C. Society	205018.6	9952060.1	2230	0.18	0.50	8.68	8.50	2.24	0.26
16	9036147	Elementaita, Soysambu Estate	188310.0	9948358.3	1819	0.18	0.43	8.76	8.95	2.81	0.24
17	9036150	Gilgil Kikopey Ranch	184600.1	9948356.8	1846	0.19	0.50	7.10	7.73	2.51	0.27
18	9036151	Subukia Pyrethrum Nursery	184589.7	9996315.2	2083	0.22	0.61	8.93	9.47	3.50	0.36
19	9036152	S. Kinangop Njabini F.T.C.	238445.7	9920723.3	2535	0.24	0.63	8.71	9.22	2.73	0.40
20	9036162	Kijabe Railway Station	231031.0	9898595.6	2119	0.12	0.52	11.39	11.87	2.39	0.20
21	9036164	S. Kinangop Forest Station	242154.1	9920725.2	2531	0.24	0.68	9.47	9.95	2.53	0.43
22	9036174	Aberdare Park Fort Jerusalem	240295.8	9942846.7	3173	0.21	0.77	7.57	8.58	2.80	0.47
23	9036179	Naivasha Korongo Farm	197605.7	9917016.2	1888	0.17	0.49	7.23	8.69	2.38	0.26
24	9036183	Naivasha Karati Scheme	227310.1	9918881.1	2546	0.20	0.59	7.44	8.81	3.43	0.33
25	9036188	Kinangop Sasumua Dam	240307.4	9917040.8	2517	0.28	0.73	8.38	10.74	2.83	0.51
26	9036198	New Gakoe Farm (Nakuru)	184593.1	9970488.0	1936	0.24	0.58	7.35	8.00	3.23	0.36
27	9036214	Naivasha Longonot Farm	208749.2	9909643.5	1897	0.14	0.50	8.62	9.69	2.74	0.21
28	9036227	Elementaita Nderit Ranger Post	180876.8	9953888.3	1828	0.21	0.53	7.05	8.00	2.61	0.31
29	9036236	Nakuru Lanet Police Post	180698.6	9966605.4	1873	0.24	0.60	6.33	7.20	2.75	0.37
30	9036241	Geta Forest Station	234725.4	9948375.4	2605	0.24	0.63	8.61	8.00	2.75	0.39
31	9036243	Dundori Forest Station	190291.0	9971381.6	2237	0.21	0.50	11.23	10.07	2.38	0.30
32	9036244	Kieni Forest Station	240313.7	9905979.6	2536	0.21	0.61	10.81	11.03	2.12	0.35
33	9036252	Menengai Forest Station	175300.5	9972334.0	2226	0.24	0.57	7.63	7.86	2.34	0.36
34	9036253	Thome Farmers No. 2	197598.3	9929928.5	2385	0.18	0.53	9.64	11.12	2.60	0.28
35	9036257	Eastern Rift Saw Mill Ltd.	244026.4	9898604.1	2336	0.21	0.49	9.07	10.43	2.99	0.29
36	9036259	Gatare Forest Station	251441.2	9920729.8	2602	0.32	0.79	11.58	13.71	2.49	0.60
37	9036261	Nakuru Meteorological Station	177161.6	9970486.3	1919	0.31	0.65	5.51	7.32	3.07	0.47
38	9036262	Olaragwai Farm Naivasha	216167.7	9928090.4	2070	0.19	0.49	7.16	7.64	2.89	0.27
39	9036264	N. Kinangop Mawingo Scheme	223589.3	9944687.8	2407	0.23	0.64	7.21	7.68	2.56	0.39
40	9036272	Mutubia Gate (A.N. Park)	236574.8	9946539.8	2643	0.34	0.70	7.75	8.62	2.61	0.54
41	9036277	Magura River	244002.9	9946542.4	3009	-	-	-	-	-	-
42	9036278	Riunge Hill	245859.8	9955756.7	3167	-	-	-	-	-	-
43	9036279	Culvert Camp	251427.4	9957605.3	2619	-	-	-	-	-	-
44	9036280	Chania River Aberd. Nat. Park	245861.5	9950226.3	2990	-	-	-	-	-	-
45	9036281	Naivasha W.D.D.	217537.8	9918237.8	2031	0.21	0.51	6.26	8.00	3.07	0.30
46	9036285	Longonot Akira Ranch	206913.5	9891210.1	1694	0.11	0.42	10.26	9.67	1.67	0.16

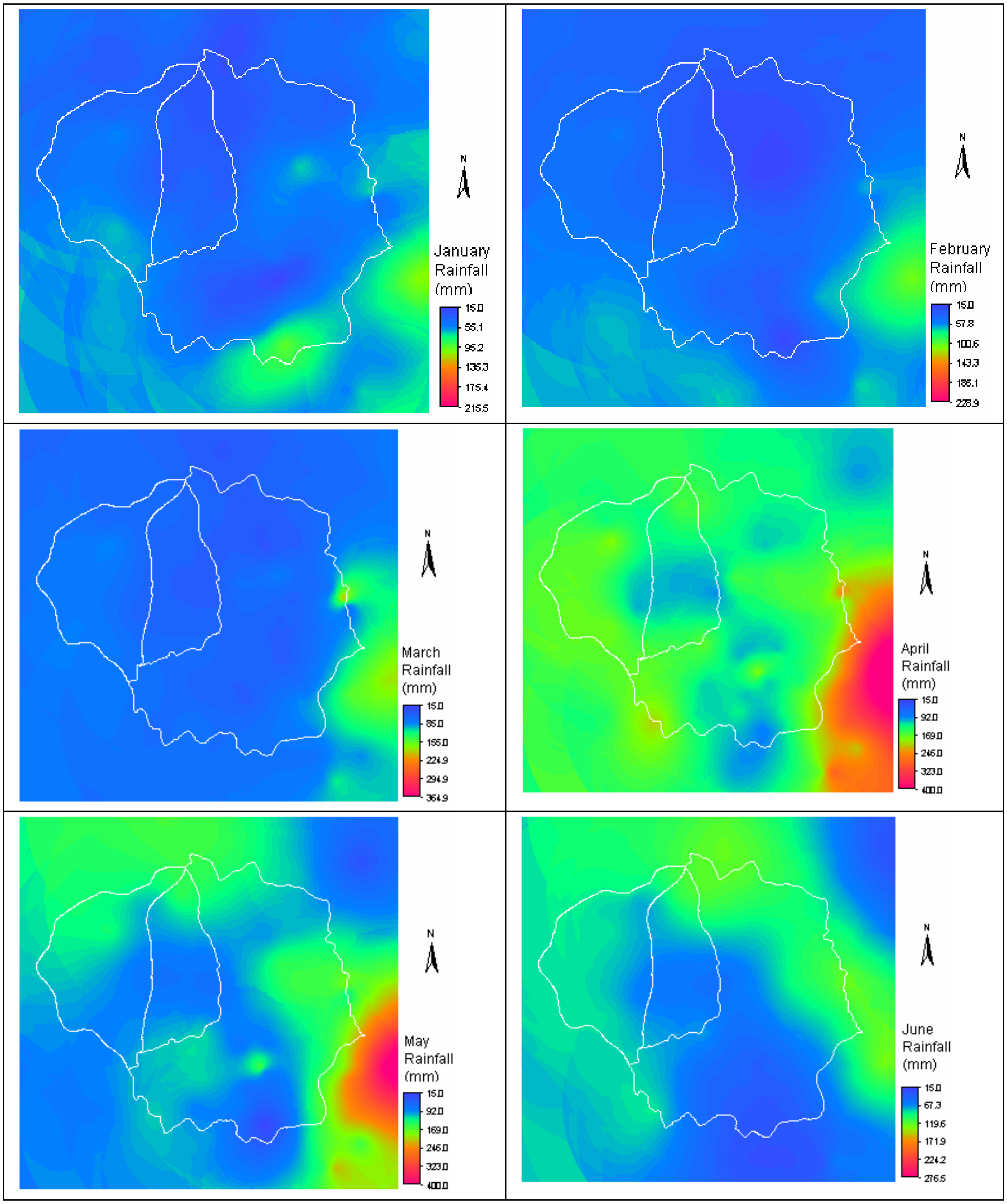
47	9036289	Wanjohi Chief's Camp	225432.9	9961281.9	2438	0.26	0.64	6.13	6.72	3.65	0.42
48	9036290	Malewa Farmer Coop. Soc.	216155.3	9959431.9	2323	0.18	0.60	6.72	7.10	2.46	0.31
49	9036294	Ngecha New Farmers Coop.	206879.6	9950213.1	2154	0.16	0.64	7.34	9.04	3.08	0.31
50	9036296	Kurase Hill Aberdare Park	240289.6	9963133.0	3347	-	-	-	-	-	-
51	9036307	Kangui Secondary School	203150.5	9987088.3	2542	0.17	0.62	9.23	10.38	3.04	0.32
52	9036308	Ngethu Water Supply	266295.5	9898617.8	1798	0.21	0.63	10.85	14.50	2.60	0.37
53	9036309	Miti Mingi Farm	177172.0	9940983.7	1908	0.24	0.55	6.57	7.93	2.76	0.35
54	9036310	Kamirithu Fancy Farm	169732.3	9961265.8	1929	0.23	0.50	10.21	16.19	4.59	0.31
55	9036312	Chamata Gate	225429.5	9977875.4	2822	0.27	0.65	6.82	8.02	2.57	0.43
56	9036313	Chebuswa Hill	232858.9	9974192.9	3229	-	-	-	-	-	-
57	9036317	Sakutiek C.C. Outpost	182763.8	9905940.9	2695	0.20	0.55	8.93	10.17	4.01	0.31
58	9036319	Mugunda Primary School	243994.9	9981561.4	2337	0.15	0.49	8.07	8.34	3.32	0.22
59	9036320	Naishi Ranger's Post	175307.3	9950201.1	1790	0.21	0.53	7.42	8.64	3.00	0.31
60	9036322	Crescent Island	210520.0	9914764.8	1881	0.16	0.44	7.38	7.85	2.63	0.22
61	9036323	Kianganye Farm Ichichi	257007.9	9922579.5	2286	0.28	0.73	14.19	15.73	2.63	0.50
62	9036331	Olchoro Agri. Office	167911.4	9907777.9	2571	0.19	0.43	9.78	10.55	2.46	0.25
63	9036336	Tumaini N.Y.S. Camp	197583.1	9970491.0	2499	0.20	0.58	9.73	10.09	2.10	0.32
64	9036337	Sururu Forest Station	169743.2	9935446.7	2551	0.20	0.51	9.71	10.24	2.67	0.29
65	9036342	Ndunyu Njeru	219877.5	9926244.8	2177	0.19	0.57	8.32	6.16	2.03	0.31
66	9036343	Olkaria Geothermal Station	199477.2	9900420.8	2031	0.19	0.44	7.81	10.01	2.72	0.25

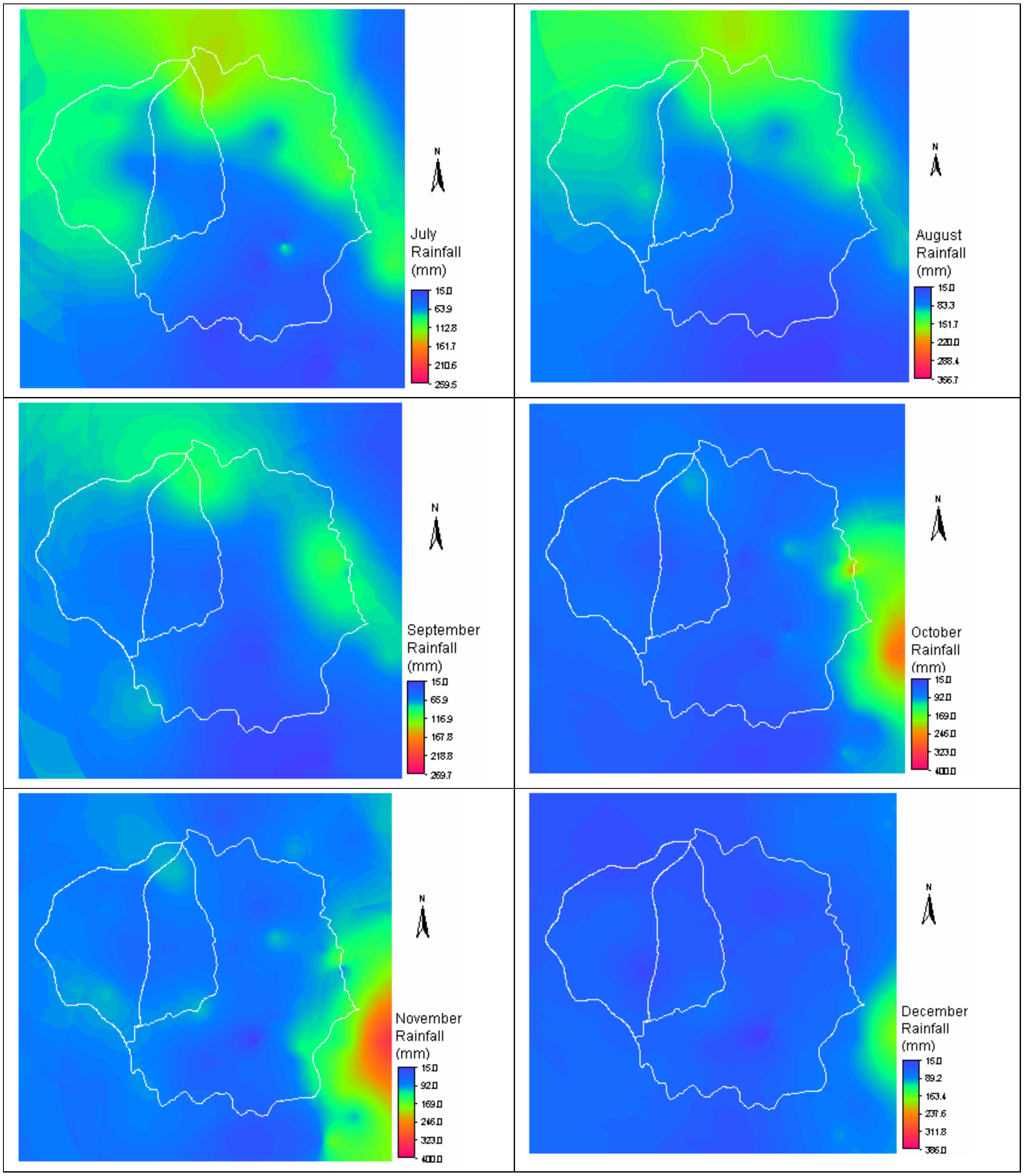
Appendix 4: Mean monthly rainfall (in mm).

	Station id	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	9036002	34.4	35.3	54.8	113.0	71.3	42.8	33.4	42.1	42.2	52.6	63.3	40.6
2	9036011	45.9	49.3	81.2	149.1	121.3	35.6	15.9	16.2	16.3	40.4	55.3	56.9
3	9036025	51.9	54.7	78.6	161.0	154.2	97.7	70.6	88.6	104.4	100.8	111.3	61.8
4	9036034	28.7	34.4	47.2	88.5	66.8	49.8	52.0	51.9	37.4	50.3	70.5	41.7
5	9036059	44.5	45.6	40.2	99.1	94.0	41.7	35.0	53.0	24.9	42.9	62.2	43.8
6	9036061	67.5	68.8	107.6	253.6	211.0	66.0	44.8	34.6	37.3	100.1	171.0	88.0
7	9036062	34.7	46.8	66.3	117.1	84.5	48.8	37.3	34.3	39.5	35.8	54.4	50.7
8	9036065	58.0	66.1	86.4	156.6	103.0	32.0	33.8	33.4	51.0	58.4	83.3	66.5
9	9036072	73.9	50.7	71.5	137.2	110.2	32.5	37.7	35.9	22.6	90.5	114.9	78.3
10	9036073	30.8	31.2	48.4	97.5	82.2	47.4	38.3	48.3	29.5	43.4	57.3	42.9
11	9036076	31.0	39.6	58.5	122.1	119.7	81.3	79.1	107.8	69.7	63.0	75.0	35.0
12	9036081	48.0	41.2	48.6	104.0	83.4	53.6	39.9	51.9	33.7	60.9	71.5	43.8
13	9036085	49.8	37.5	77.4	107.0	63.9	25.9	43.5	50.4	33.0	55.9	101.5	91.8
14	9036109	40.9	39.0	48.9	107.6	80.0	48.4	43.0	50.7	32.9	47.6	65.3	45.5
15	9036129	35.1	29.0	51.0	107.7	87.4	58.6	66.3	96.6	49.5	70.9	88.0	49.0
16	9036147	43.8	35.4	46.6	102.7	77.9	65.1	56.7	75.3	55.7	52.7	68.3	46.3
17	9036150	28.2	35.1	51.8	107.4	72.4	47.5	51.6	65.3	44.8	53.1	70.2	45.7
18	9036151	36.4	35.4	48.9	146.3	157.5	101.3	122.8	150.7	87.3	75.9	90.8	37.0
19	9036152	65.9	68.8	109.2	206.1	176.4	70.2	54.4	62.6	58.4	116.0	131.5	70.6
20	9036162	41.9	44.2	66.6	150.5	126.8	32.3	23.8	16.9	24.1	36.4	73.9	71.9
21	9036164	71.9	81.1	141.0	248.2	213.7	80.9	64.5	61.9	56.3	125.0	159.0	80.3
22	9036174	28.3	38.4	72.5	148.4	110.8	89.7	88.9	87.8	87.3	112.9	89.8	46.3
23	9036179	28.1	28.6	52.1	107.8	110.0	51.6	48.5	44.0	36.4	41.6	50.7	39.1
24	9036183	58.9	60.0	69.9	126.7	115.9	43.6	33.7	34.2	56.3	77.2	94.2	66.7
25	9036188	70.0	77.6	137.8	263.7	231.6	88.0	61.7	57.5	50.9	131.2	169.3	85.8
26	9036198	31.8	33.6	55.3	132.8	111.6	84.4	86.5	93.3	80.9	81.0	103.1	40.5
27	9036214	38.7	43.4	61.8	117.8	82.8	38.3	30.0	34.2	39.2	50.5	56.2	42.0
28	9036227	30.5	31.7	54.4	113.5	84.6	67.7	67.8	91.1	60.3	50.4	71.8	41.6
29	9036236	40.3	39.0	54.8	118.1	101.8	65.0	69.2	83.3	66.7	76.2	70.8	40.1
30	9036241	55.2	43.3	69.2	157.9	152.8	114.7	102.3	109.5	125.1	108.0	96.2	48.6
31	9036243	24.3	30.6	55.8	139.2	145.9	116.8	122.0	125.7	97.4	101.4	110.7	38.6
32	9036244	58.5	62.2	113.3	265.6	213.0	65.5	44.5	46.6	41.4	112.4	174.2	79.4
33	9036252	40.8	34.9	61.9	132.9	120.9	80.7	90.0	106.7	88.0	82.3	91.4	35.9
34	9036253	45.2	44.4	60.5	152.7	113.1	67.2	56.3	79.2	42.1	60.2	98.7	79.7
35	9036257	51.1	55.3	87.0	166.9	139.4	41.3	30.5	26.0	35.3	68.7	98.6	63.3
36	9036259	104.6	101.3	158.8	344.3	351.4	139.5	100.2	102.2	82.7	222.4	282.6	143.8
37	9036261	33.6	39.8	62.9	124.8	112.3	75.6	87.9	106.3	82.1	71.3	73.6	35.9
38	9036262	38.2	42.9	52.5	112.8	79.7	57.5	40.4	53.9	38.2	59.1	66.2	42.9
39	9036264	45.3	36.9	48.9	158.8	148.1	96.9	75.9	90.3	77.9	83.0	81.9	38.6
40	9036272	63.7	74.9	104.8	188.7	162.6	139.1	108.9	133.6	129.4	166.4	133.2	68.8
41	9036277	7.6	0.0	10.8	0.0	13.0	0.0	3.8	1.9	0.0	8.9	0.0	2.5
42	9036278	4.6	0.0	8.9	0.0	13.3	0.0	2.0	2.2	0.0	5.7	0.0	2.5

43	9036279	5.1	0.0	6.8	0.0	9.8	0.0	3.5	1.3	0.0	2.5	0.0	3.1
44	9036280	12.7	0.0	9.5	0.0	12.0	0.0	1.8	3.8	0.0	10.2	0.0	2.5
45	9036281	40.4	43.0	60.9	109.7	75.2	44.7	35.8	40.1	36.6	59.4	68.0	41.2
46	9036285	66.1	69.0	62.4	99.6	87.5	37.8	28.2	17.7	23.8	23.7	38.0	37.8
47	9036289	39.2	27.3	46.0	119.2	105.7	97.4	93.9	112.2	79.4	71.2	72.0	37.1
48	9036290	40.2	23.6	40.4	107.3	86.0	85.9	66.0	79.4	61.4	58.6	53.5	27.9
49	9036294	60.4	9.9	57.5	152.0	100.8	56.3	52.7	82.9	45.1	30.4	64.9	42.4
50	9036296	5.70	0.00	3.47	0.00	4.23	0.00	15.93	4.23	0.00	4.23	0.00	2.45
51	9036307	18.5	31.4	37.4	101.7	138.7	115.8	125.4	174.3	78.8	56.6	46.4	36.6
52	9036308	56.5	31.8	90.6	250.3	178.0	57.3	38.0	31.8	32.4	115.8	204.1	98.5
53	9036309	43.1	38.5	53.4	103.1	93.4	70.2	77.7	99.2	62.4	57.8	68.4	21.5
54	9036310	40.2	35.5	54.4	128.3	112.2	92.0	82.7	100.7	58.5	53.2	82.5	32.4
55	9036312	39.4	31.4	55.1	139.9	114.6	97.3	111.7	142.3	69.3	64.2	102.9	69.3
56	9036313	0.0	0.0	0.0	0.0	-	49.4	-	0.0	0.0	0.0	-	-
57	9036317	51.7	58.3	49.2	217.4	114.5	92.0	41.3	56.8	83.1	60.6	98.0	37.9
58	9036319	49.9	34.2	58.9	84.6	32.3	43.7	55.6	46.4	29.4	57.4	72.6	68.9
59	9036320	40.1	40.2	54.3	118.7	89.4	86.0	60.5	85.0	54.5	49.6	62.8	50.9
60	9036322	37.1	34.5	47.6	98.3	65.7	50.0	35.0	31.6	34.6	49.3	67.8	39.7
61	9036323	108.8	72.7	137.0	353.9	347.0	126.6	83.7	95.4	79.5	220.2	287.4	161.6
62	9036331	63.9	70.4	68.0	122.6	78.9	76.8	63.2	78.6	63.7	47.7	66.6	59.3
63	9036336	26.5	20.7	41.3	145.6	127.4	114.9	131.8	135.5	95.2	92.0	83.8	37.9
64	9036337	65.2	44.7	76.0	137.1	88.9	74.7	90.9	81.8	56.3	73.6	104.3	49.0
65	9036342	14.7	30.0	46.7	137.7	93.6	67.1	90.0	78.8	80.2	102.6	94.9	61.8
66	9036343	57.6	53.6	60.4	119.7	88.0	41.9	21.0	31.6	26.7	41.4	78.3	45.1
67	Geta	-	-	-	-	11.9	23.8	31.7	47.5	26.1	32.7	28.4	14.2
68	Kedong	107.3	3.0	73.3	80.9	11.2	16.5	47.9	26.7	22.3	45.5	59.1	54.1
69	Mutubio	86.1	70.0	202.6	268.0	191.7	120.8	97.4	143.2	23.9	245.5	173.3	49.5
70	NkinHos	16.2	2.0	36.3	40.9	44.9	-	-	-	0.3	61.1	35.3	6.3
71	La_belle	2.3	30.0	55.4	98.7	193.7	27.7	22.4	29.7	2.6	24.4	1.3	0.3
72	Kipipiri	76.5	20.7	79.8	163.2	151.8	80.7	88.6	100.3	69.7	111.8	116.6	58.5

Appendix 5: Cokriging predicted mean monthly rainfall maps with elevation.




N
July
Rainfall
(mm)
15.0
63.9
112.8
161.7
210.6
259.5
N
August
Rainfall
(mm)
15.0
83.3
151.7
220.0
288.4
356.7
N
September
Rainfall
(mm)
15.0
65.9
116.9
167.8
218.8
269.7
N
October
Rainfall
(mm)
15.0
92.0
169.0
246.0
323.0
400.0
N
November
Rainfall
(mm)
15.0
92.0
169.0
246.0
323.0
400.0
N
December
Rainfall
(mm)
15.0
89.2
163.4
237.6
311.8
386.0

Appendix 6: Mean annual rainfall.

	St_Id	St_Name	X cord. (m)	Y cord. (m)	Elev. (m)	Rainfall (mm)
1	9036002	Naivasha D. O.	215437.2	9919909.6	1962	646.1
2	9036011	Kedong Valley, Maai Mahiu	232895.8	9891229.7	1869	756.0
3	9036025	N. Kinangop Forest Station	236579.1	9935478.3	2661	1160.5
4	9036034	Gilgil Railway Station	201658.3	9945330.7	2005	624.0
5	9036059	Kangari Farm, Naivasha	219876.6	9928092.2	2209	639.9
6	9036061	Kirita Forest Station	236604.1	9891232.3	2403	1383.4
7	9036062	Naivasha Kongoni Farm	195030.7	9908737.5	2002	679.4
8	9036065	Naivasha Nanga Gerri	225452.3	9915185.3	2383	856.4
9	9036072	Mweiga Estate	268129.7	9961292.3	1912	904.1
10	9036073	Naivasha K.C.C. Ltd.	208739.3	9926239.0	1899	621.8
11	9036076	Technology Farm, Nakuru	167881.0	9966798.7	1913	914.6
12	9036081	Naivasha Vet. Expt. Station	212458.6	9928088.5	1925	733.9
13	9036085	Karameno Shopping Centr, N/Moru	251422.5	9985256.4	2060	777.8
14	9036109	Naivasha Marula Estate	207669.4	9927124.8	1890	680.6
15	9036129	Chokerereia F.C. Society	205018.6	9952060.1	2230	812.2
16	9036147	Elementaita, Soysambu Estate	188310.0	9948358.3	1819	753.0
17	9036150	Gilgil Kikopey Ranch	184600.1	9948356.8	1846	686.6
18	9036151	Subukia Pyrethrum Nursery	184589.7	9996315.2	2083	1149.5
19	9036152	S. Kinangop Njabini F.T.C.	238445.7	9920723.3	2535	1245.7
20	9036162	Kijabe Railway Station	231031.0	9898595.6	2119	805.6
21	9036164	S. Kinangop Forest Station	242154.1	9920725.2	2531	1475.4
22	9036174	Aberdare Park Fort Jerusalem	240295.8	9942846.7	3173	1040.6
23	9036179	Naivasha Korongo Farm	197605.7	9917016.2	1888	662.2
24	9036183	Naivasha Karati Scheme	227310.1	9918881.1	2546	878.5
25	9036188	Kinangop Sasumua Dam	240307.4	9917040.8	2517	1555.0
26	9036198	New Gakoe Farm (Nakuru)	184593.1	9970488.0	1936	962.1
27	9036214	Naivasha Longonot Farm	208749.2	9909643.5	1897	671.9
28	9036227	Elementaita Nderit Ranger Post	180876.8	9953888.3	1828	789.5
29	9036236	Nakuru Lanet Police Post	180698.6	9966605.4	1873	846.5
30	9036241	Geta Forest Station	234725.4	9948375.4	2605	1214.4
31	9036243	Dundori Forest Station	190291.0	9971381.6	2237	1176.9
32	9036244	Kieni Forest Station	240313.7	9905979.6	2536	1373.3
33	9036252	Menengai Forest Station	175300.5	9972334.0	2226	992.0
34	9036253	Thome Farmers No. 2	197598.3	9929928.5	2385	971.6
35	9036257	Eastern Rift Saw Mill Ltd.	244026.4	9898604.1	2336	931.4
36	9036259	Gatare Forest Station	251441.2	9920729.8	2602	2509.5
37	9036261	Nakuru Meteorological Station	177161.6	9970486.3	1919	934.8
38	9036262	Olaragwai Farm Naivasha	216167.7	9928090.4	2070	696.9
39	9036264	N. Kinangop Mawingo Scheme	223589.3	9944687.8	2407	1007.5
40	9036272	Mutubia Gate (A.N. Park)	236574.8	9946539.8	2643	1513.6
41	9036277	Magura River	244002.9	9946542.4	3009	115.1
42	9036278	Riunge Hill	245859.8	9955756.7	3167	62.0
43	9036279	Culvert Camp	251427.4	9957605.3	2619	37.3
44	9036280	Chania River Aberd. Nat. Park	245861.5	9950226.3	2990	77.9
45	9036281	Naivasha W.D.D.	217537.8	9918237.8	2031	681.4
46	9036285	Longonot Akira Ranch	206913.5	9891210.1	1694	610.1
47	9036289	Wanjohi Chief's Camp	225432.9	9961281.9	2438	922.3
48	9036290	Malewa Farmer Coop. Soc.	216155.3	9959431.9	2323	743.8
49	9036294	Ngecha New Farmers Coop.	206879.6	9950213.1	2154	809.8
50	9036296	Kurase Hill Aberdare Park	240289.6	9963133.0	3347	40.3

51	9036307	Kangui Secondary School	203150.5	9987088.3	2542	1043.7
52	9036308	Ngethu Water Supply	266295.5	9898617.8	1798	1454.7
53	9036309	Miti Mingi Farm	177172.0	9940983.7	1908	812.9
54	9036310	Kamirithu Fancy Farm	169732.3	9961265.8	1929	1162.1
55	9036312	Chamata Gate	225429.5	9977875.4	2822	1056.3
56	9036313	Chebuswa Hill	232858.9	9974192.9	3229	49.4
57	9036317	Sakutiek C.C. Outpost	182763.8	9905940.9	2695	1015.3
58	9036319	Mugunda Primary School	243994.9	9981561.4	2337	657.0
59	9036320	Naishi Ranger's Post	175307.3	9950201.1	1790	821.6
60	9036322	Crescent Island	210520.0	9914764.8	1881	599.1
61	9036323	Kianganye Farm Ichichi	257007.9	9922579.5	2286	2580.9
62	9036331	Olchoro Agri. Office	167911.4	9907777.9	2571	919.6
63	9036336	Tumaini N.Y.S. Camp	197583.1	9970491.0	2499	1118.6
64	9036337	Sururu Forest Station	169743.2	9935446.7	2551	1008.8
65	9036342	Ndunyu Njeru	219877.5	9926244.8	2177	906.0
66	9036343	Olkaria Geothermal Station	199477.2	9900420.8	2031	715.6
67	Kipipiri	Kipipiri	219866.6	9952065.2	2303	1133.2
68	Geta	Geta	222500.0	9958889.0	2513	216.2
69	Kedong	Kedong	215555.6	9903889.0	2111	547.6
70	La_belle	La belle	214194.1	9921152.8	1897	616.1
71	Mutubio	Mutubio	238888.9	9945278.0	3129	1671.9
72	NKinHos	N. Kinangop Cath. Hospital	229027.8	9940556.0	2458	243.2

Appendix 7: Regression kriging predicted mean annual rainfall map with DEM.