Rainfall interpolation using a remote sensing CCD data in a tropical basin – A GIS and geostatistical application

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Abstract

This paper is aimed at developing a geostatistical model to improve interpolated annual and monthly rainfall variation using remotely-sensed cold cloud duration (CCD) data as a background image. The data set consists of rainfall data from a network of 704 rain gauges in the Rufiji drainage basin in Tanzania. We found ordinary kriging to be a robust estimator due mainly to its inherent nature of including the non-stationary local mean during estimation. Parameter sensitivity analysis and examination of the residuals revealed that the parameter values of the variogram viz., the nugget effect, the range, sill value and maximum direction of continuity, as long as they are in acceptable ranges, and any different combination of these parameters, have low effect on model efficiency and accuracy. Rather, the use of remotely-sensed CCD data as a background image is found to improve the interpolation as compared to the estimation based on observed point rainfall data alone. The study revealed the improvement in terms of Nash–Sutcliffe model performance index (R^2) by using CCD as external drift with kriging provided an R^2 of 64.5% compared to the simple kriging and ordinary kriging, which performed with efficiency of 60.0% and 61.4%, respectively. For each case, parameter sensitivity analysis was conducted to investigate the effect of the change in the parameters on the model performance and the spatio-temporal interpolation results.

Keywords: Kriging; Cold cloud duration (CCD); Parameter sensitivity; Variogram analysis

1. Introduction

The development of a model to reproduce observed rainfall variation in space and time and its relationship with remote-sensing based rain-producing cloud information in the basin is of particular interest to understanding atmosphere–ecosystem interaction in a typical tropical climatic region of Africa. This signifies the importance of spatially interpolated rainfall data as the main input of the hydrological cycle and water balancing at a watershed or basin scale. Possible improvement in rainfall interpolation at a basin scale using the time-series of the cold cloud duration (CCD) data are reported by several authors (e.g. Grimes and Diop, 2003). The link between rainfall and vegetation dynamics in-turn advances our understanding of various crop growth dynamics and agricultural production for large areas (e.g. Hill and Donald, 2003; Reynolds et al., 2000; Diallo et al., 1991; Sannier et al., 1998; Kobayashi and Dye, 2005).

The significance of spatial distribution of rainfall and its effects on spatial correlation functions are reviewed in Bacchi and Kottegoda (1995). The same authors review a number of statistical terms and properties with reference to the theory of variograms originally adopted in geostatistics. The association of small time step rainfields and strong spatial variability in the convective nature of tropical rainfalls is investigated in Amani and Lebel (1998). This situation undermines the interpolation of connective rainfall by classical two-dimensional (2D) algorithms. Rather, Amani and Lebel (1998) developed a lagrangian approach, based on interpolation of arrival times of rainfall.

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Daily rainfall is measured in the Rufiji basin at a number of sites (point measurements) but often it is necessary to estimate average areal rainfall over an area of interest. This can be done by various methods of spatial interpolation such as simple arithmetic average, Thiessen polygon, and kriging. The arithmetic mean value or values that are based on other spatial interpolation techniques do not address the variation in all climatic zones of the basin. For instance, the Thiessen polygon method provides spatial variation that depends only on distances between stations for such large drainage basins of complex hydroclimatology. This work is concerned with the application of kriging, which is a geostatistical interpolation technique that considers other factors that affect rainfall processes and the spatial variation of rainfall measurements.

In this study we explore the suitability of kriging techniques for spatial interpolation of rainfall with a view to achieve the following objectives: (i) to identify the most suitable kriging model for interpolation of rainfall in a tropical watershed, the Rufiji basin, (ii) to establish a suitable set of variogram parameters for future use in the basin, (iii) to develop a custom built, fully automated, computer program of rainfall interpolation for the Rufiji basin based on the results of the previous two steps, and (iv) to investigate the use of freely available cold cloud duration data (CCD) to improve the spatial interpolation of rainfall given that maintenance of manual rain gauges is gradually becoming difficult.

The goal of this study was to use CCD remotely sensed data and field rainfall data to obtain a spatially consistent rainfall map over a large drainage basin that could be used for hydrological and water resources modelling for the Rufiji Drainage Basin in Tanzania (Fig. 1). In this study various deterministic geostatistical techniques are investigated and implemented for spatial data interpolation. These include kriging (K), cokriging (CK), kriging with an external drift (KED) (Deutsch and Journel, 1998; Goovaerts, 1997). We selected these three instructive approaches, namely K, CK and KED from Deutsch and Journel (1998) and Goovaerts (1997) to investigate their performance in terms of model efficiency and other uncertainty criteria.

The use of satellite infrared imagery for rainfall analysis is very important for at least two reasons. First, current sparse rain gauge networks over central portions of the basin do not provide the basic resolution required to describe the spatial distribution of rainfall over the basin. Secondly, the background spatially distributed data estimated from satellite data can be employed to estimate the rainfall distribution and hence maintaining the heterogeneity of rainfall over the basin.

2. The study area

The Rufiji River basin lies between longitudes 32.5° and 40° East and latitudes 5.5° and 10.5° South. It is the largest river basin in Tanzania (Fig. 1) covering an area of about

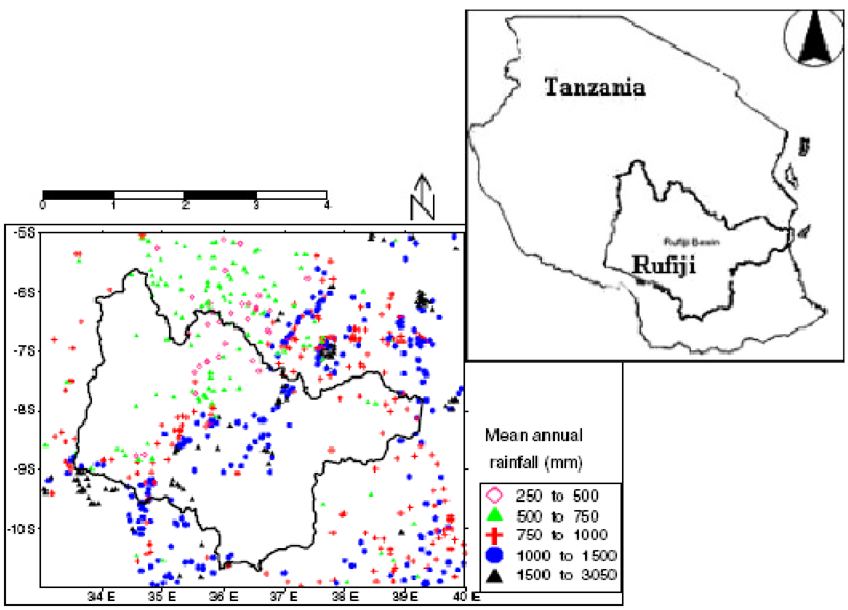

Fig. 1. Distribution of raingauge stations in the Rufiji basin and with their mean annual rainfall in mm. The symbols represent rain gauge stations and indicated amounts of MAP.

177,000 km^2 and extending 700 kms from Mbeya region in the West to the Indian Ocean in the East. The Rufiji River basin consists of three sub-basins; the Great Ruaha, the Leivegu, and the Kilombero sub-basin which constitute 47%, 18%, and 20%, respectively, of the total area of the Rufiji basin. The basin is situated predominantly in the semi-arid belt, which runs from North to South through the central portion of Tanzania. The land cover of the study area is dominated by 92 scattered forest reserves in the Rufiji basin, in which 47.5% is forest and woodland, 43.6% is bush land and grassland, 6.5% is cultivated, and the remaining 3% is open land and water bodies as compiled from the data of Ministry of Agriculture (MOA) MOA (1987).

3. Methods and materials

3.1. Methodology

Kriging is a technique that estimates a variable Z at an unsampled location, u, from observed values at the neighbouring locations, u_α. The simplest forms of kriging models relate $Z(u)$ to $Z(u_\alpha)$ by linear regression. The regression parameters are calibrated to minimize the variance of the error estimation, Var $(Z(u) - Z(u_\alpha))$, under the constraints that the expected value $E[Z(u) - Z(u_\alpha)]$ is equal to zero.

Mathematical details of the various techniques are presented in Deutsch and Journel (1998) and Goovaerts (1997). Kriging with an external drift, KED, is a variant of kriging that allows for the use of secondary information known at every location (exhaustive), which is assumed to reflect the local spatial trend of the primary variable (Deutsch and Journel, 1998; Goovaerts, 1997). A well-researched account of the history and origins of kriging can be found in Cressie (1990), Cressie (1991) and Kitanidis (1997).

In general, spatial variation can be decomposed into two components, large-scale variation, and small-scale variation. The KED trend represents the large-scale variability of the primary variable. The residuals from the trend represent the small-scale variability, and the final KED result combines both. KED models the trend under the assumptions of a linear relationship between primary and secondary variables and smooth variation in the secondary variable. The distinctive feature of KED is that the algorithm employs a non-stationary random function model, where stationarity is limited within each search neighbourhood, yielding more local detail than with ordinary kriging (Deutsch and Journel, 1998).

The KED estimator from Deutsch and Journel (1998) is given by the equation

$$Z^*_{\mathrm{KED}}(u) = \sum_{\alpha=1}^{n(u)} \lambda_\alpha^{\mathrm{KED}}(u) Z(u_\alpha) \tag{1}$$

where $Z^*_{\mathrm{KED}}(u)$ is the KED estimator at location u, $\lambda_\alpha^{\mathrm{KED}}(u)$ are the KED weights (W_i) corresponding to the n samples at location u, and $Z(u_\alpha)$ are the sample values within the search neighbourhood.

Kriging provides optimal estimation, relative to other interpolation methods, in the sense that it minimizes the least-square error for a covariance model with the unbiased condition. The kriging weights (W_i), which are represented by $\lambda_\alpha^{\mathrm{KED}}(u)$ in Eq. (1), depend on the positions of observed and calculated points and the number of observations. The observed points are stations with recorded rainfall data while calculated points are stations of geo-referenced pixels or grids at which interpolated values are assigned. The interpolated and geo-referenced pixel or grid values of rainfall data for each time step is then archived and manipulated in Geographic Information System (GIS). The kriging covariance, C, used in this study employs spherical model to fit the actual covariance calculated from annual spatial rainfall data. For monthly rainfall data, the Gaussian, spherical and the exponential models were also employed, from which the best model was selected based on optimization of model fit.

3.2. Rainfall data

The rainfall data is obtained from the Hydrological Database of the Water Resources Engineering Department of the University of Dar es Salaam. The spatial distribution of the rainfall observation stations in Rufiji basin is uneven. In the upper and lower reaches of Rufjij basin the distribution of stations is sparse. To fill this gap, stations near or around the basin are also included in the analysis (Fig. 1).

Rainfall records for 704 stations located in the basin were applied. The record length at these stations is also uneven and a summary is given in Fig. 2. Average monthly and annual rainfall records for from varying years of record starting for some stations during the 1910s, and most stations ending during the 1990s and some extending up to 2000 were available and were used in the study.

It was difficult to find a large number of stations in the basin with concurrent records due to the fact that CCD is

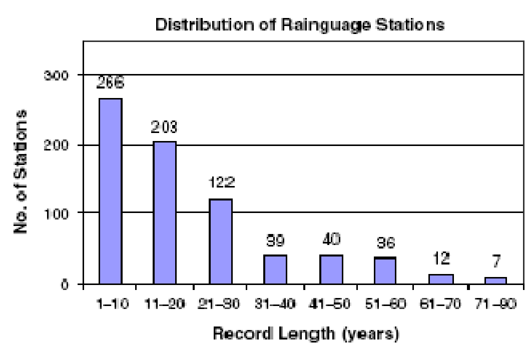

Fig. 2. Summary details of the rainfall data used in the study.

the recent phenomena of remote sensing data on the one hand and recorded rainfall data is not updated as long as CCD records on the other hand. Although it seems inaccurate to use these data of different record lengths, the give a good indication of existence of the underlying relation between the primary variable under study (rainfall) and CCD as a secondary variable over the basin.

3.3. Cold cloud duration (CCD) data

Cloud cover information is a huge database collected every few or fraction of a minute from satellite platforms by remote sensing techniques. This huge information is analyzed and rainfall-producing cold cloud is calibrated, validated and distributed freely from different sources. Cold cloud duration (CCD) is duration or a period over which a rainfall-producing cloud with apparent temperature lower than predetermined threshold (calibrated) as a rainfall-producing event is observed in a location. These temperatures are calibrated and validated from sufficient pairs of sample data of CCD and rainfall events referring to similar periods and locations. Rainfall is estimated from CCD using calibration coefficients (Grimes and Bonifacio, 1999), which are prone to different errors.

The most common period widely used to disseminate CCD data is on the basis of ten days of accumulated hours of cold cloud. Ten day composite time series of CCD data from 1989 to 1996 were used to resample the long term monthly and annual average data at spatial grid resolution of 7.6 km. The data is obtained from the FAO's ARTEMIS (Africa Real Time Environmental Monitoring Information System), which is part of the FAO's use of satellite remote sensing techniques to improve the surveillance and forecasting capabilities of its Global Information and Early Warning System (GIEWS).

4. Results and discussion

4.1. Variogram analysis

Existence of any major spatial continuity in a specific direction was investigated using variogram mapping or two-dimensional variogram maps, which can show the continuity or variability of the variable along x- and y-directions. This kind of modelling helps in selecting different distance of influence (range) depending on the continuity of the variable in different directions. In general, due to the prevailing physical, topographical, and hydrological conditions of the area, the variation of rainfall in a certain direction might significantly or abruptly change with distance whilst in other direction it may change smoothly or gradually, necessitating the application of different ranges or search radii in different directions.

From the initial assessment of spatial continuity, the north-easterly direction revealed maximum variogram continuity for the Rufiji basin. In the absence of well spread (spaced) sampled data, and existence of no definitive background causes that bring rainfall variability in this north-easterly direction, we examined other spatial continuity evaluations. After routine exercises of variogram modelling, and subsequent kriging and sensitivity analysis, we found out that the effect of considering specific direction in modelling has little impact on the estimated value and we opted to adopt a reasonable range (a range less than that revealed by the maximum directional continuity). This helped us to settle with a choice of Omni-directional (or same range in all directions) variogram to be adopted in our study.

Instead of visual (manual) fitting a theoretical function of positive definite model in the considered geostatistical model studied, an interactive fitting of the nested model by Indicative Goodness Fit (IGF) criteria (Pannatier, 1996) was used. The IGF is a dimensionless quantity that can be used to judge the performance of a given variogram whose value, if it approaches zero indicates a good fit. However, Pannatier (1996) cautions that this measure is not an exhaustive measure rather it gives an indication of how well the experimental and the nested model are fitted. Table 1 summarizes variogram analysis results of mean annual as well as average monthly rainfall for Rufiji basin, which was established using optimal values of IGF. The parameters obtained by fitting the best model are also given in Table 1. The parameters of these variogram models are adopted for kriging modelling and analysis of spatial rainfall interpolation in the Rufiji basin.

4.2. Kriging analysis

The algorithm of kriging calls for parameters derived from the variogram analysis; such as nugget effect, sill, range (h_{max}), major direction of continuity, and the type of best structure of the variogram. These parameters are given in Table 1.

Table 1
Optimized variogram model parameters for average monthly and mean annual rainfall in Rufiji basin

Month	Model parameters				IGF
	Model	Nugget	Sill	Range	
January	GM	0.42	0.26	0.71	0.04
February	SPH	0.36	0.30	0.54	0.10
March	EXP	0.37	0.34	0.54	0.09
April	SPH	0.41	0.44	0.71	0.06
May	SPH	0.21	0.52	0.62	0.08
June	SPH	0.33	0.51	0.77	0.04
July	EXP	0.35	0.59	0.54	0.02
August	SPH	0.37	0.47	0.40	0.02
September	EXP	0.35	0.42	0.34	0.11
October	EXP	0.50	0.26	0.50	0.12
November	EXP	0.56	0.51	1.39	0.02
December	EXP	0.34	0.49	0.31	0.05
Annual	SPH	0.42	0.50	0.90	0.01

Key. GM – Gaussian model; SPH – spherical model; EXP – exponential model.

Applicability of different kinds of kriging techniques is investigated for Rufiji basin. These include simple kriging (SK), ordinary kriging (OK), kriging with external drift (KED) and cokriging (CK). The modelling process was carried out into two steps; cross validation analysis and the over all rainfall estimation.

Cross validation of variogram models involves suppressing sample values $Z(u_\alpha)$ (Eq. (1)) one at a time and using the remaining samples and the theoretical (fitted variogram) model to estimate the missing (suppressed) value, calculating the error associated with each estimate, that is, the difference between the true (measured) and the estimated value (Eq. (1)) and using the results to determine the best model parameters (Table 1). This process is iterative. Different criteria are used to determine the validity of varigram models. In our case a comparison of the estimated and observed values was made on the basis of the Nash and Sutcliffe (1970) model efficiency criterion given by the index R^2. This index is used to identify and select the overall robust estimator, to evaluating the degree of performance of the estimator and to undertake model parameter sensitivity analysis in this modelling study.

As part of selecting the robust estimator, the ranges of acceptable parameters have been identified from preliminary variogram modelling exercise. Automatic calibration has been carried out for each kriging type for positive values starting from 0.0 and incremented by 0.1. Range of values considered for each parameter is given as nugget effect of 0.0–1.0, and sill value of 0.0–1.0.

Using the modelled variogram parameters, the exercise of selecting robust estimator and subsequent kriging was done under varying search radii and different number of neighbouring samples. The results of the R^2 values obtained are given in Table 2. Over all ordinary kriging (OK) with the corresponding variogram model parameters indicated in Table 2 have been found to be robust estimator for the Rufiji basin.

This method of automatic selection of the robust estimator and parameters by using R^2 is the best way for modelling of the parameters. It can also help investigate the sensitivity of the variogram parameters on the model outputs and performance of the variogram model.

Table 2
Model performance efficiency of different kriging types of the variogram model parameters for Rufiji basin

Estimator	Nugget	Sill	Range h_{max}	Search radius	Efficiency (R^2) (%)
Simple kriging	0.43	0.52	0.706	1.0	60.0
Ordinary kriging	0.43	0.52	0.706	1.0	61.4
Kriging with Drift	0.43	0.52	0.706	1.0	59.3

4.3. Parameter sensitivity analysis

In order to investigate the effect of the change of parameters on the estimated values, we have undertaken parameter sensitivity analysis on each of the parameters. The sensitivity evaluation was carried out on the basis of the sensitivity measured as a function of changes in the value of the model efficiency, R^2.

Firstly, effect of each variogram parameters were investigated using automatic calibration method and secondly, by using the best variogram parameters, the effect of the number of the neighbouring stations and the search radius on the kriging results is investigated. It can be clearly seen from Fig. 3 that under circumstances of acceptable ranges, (where the nugget effect is less than 0.5), the R^2 values are less sensitive to all parameter combinations.

The effect on the model efficiency R^2 and the performance of the variogram model for different search radii and size of neighbouring data is shown in Table 3. The parameters of the spherical variogram model are for Nugget, Sill and Range values are 0.42, 0.50 and 0.90, respectively. From Table 3 it can be seen that the number of the neighbouring points has more pronounced impact on the model efficiency than the search radius.

In both cases, the relative changes of the R^2 values are low and do not have any significant impact on the value of the estimated parameters of the variogram model. However, it was noticed that when the search radius is much lower than the necessary radius (in this case one degree), most of the grids remain un-estimated where as larger search radius smoothes the estimated mean annual surface. In the case of the neighbouring data sets; when the number

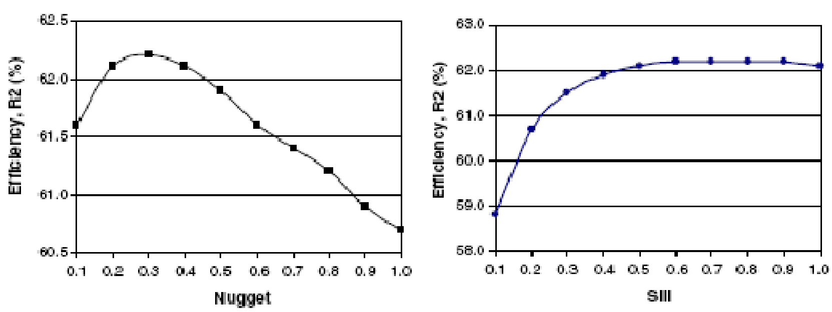

Fig. 3. Sensitivity of variogram model parameters.

Table 3
The parameter of the fitted variogram model for different search radius considered

Simulation cases	Number of neighbouring stations	R^2 (%)	Search radius (degree)	R^2 (%)
Case 1	1–5	58.5	0.5	61.4
Case 2	1–10	60.0	1.0	61.4
Case 3	1–20	61.4	2.0	61.3

of data considered in estimating a point is more, the estimate will be smoothened out but when the data considered is less, one might miss the details of the features and the estimate might be undesirable. Caution should be taken in selecting the radius of search and the number of neighbouring data.

The insensitivity of R^2 for different combination of the parameters was insightful to the investigation of other techniques or making an attempt of including other related physical or hydrological phenomena that attribute to rainfall variation and its spatial modelling.

4.4. Model reliability and residual error analysis

In order to investigate the performance of the geostatistical model for rainfall interpolation, the randomness of residuals were studied using two types of residual analysis. These are frequency histograms of the errors and error distribution plot against the estimated rainfall.

The frequency histograms of the error is shown in Fig. 4, which shows the relative frequency of error values for the Rufiji basin. Superimposed on the histogram of Fig. 4 is the plot of an ideally expected normal probability density function (pdf) curve. These plots are fairly normal with little tendency of positive skewness, showing the number of overestimation is slightly higher than the under estimation.

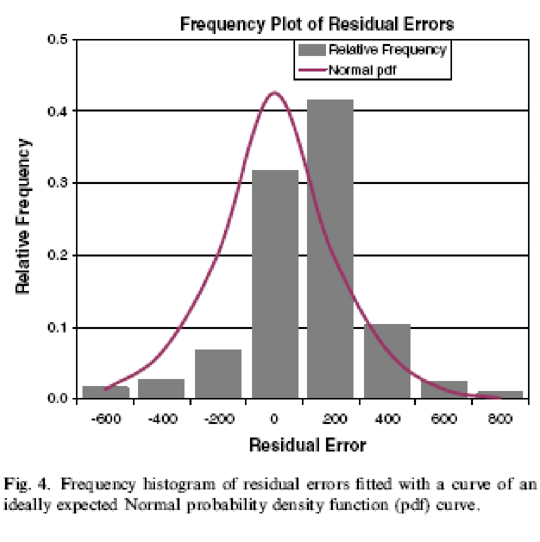

Fig. 4. Frequency histogram of residual errors fitted with a curve of an ideally expected Normal probability density function (pdf) curve.

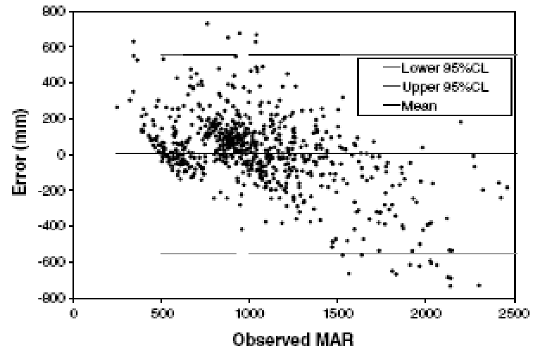

Fig. 5. Observed mean annual rainfall (MAR) versus model errors.

The distribution of the error (observed minus simulated values) was plotted against observed mean annual rainfall (Fig. 5). Even though, the distribution of the errors has fallen well within the lower and upper bounds limits of the 95% confidence limits, the plot shows a seemingly systematic relation between the observed and error quantity, whereby lower values are in general underestimated and higher values are overestimated (Fig. 5).

In the least square sense of model efficiency and based on this investigation (parameter sensitivity and residual analysis) further improvement can only be achieved if extra secondary variable which is known to have relation with the rainfall quantity might be included in the analysis such as CCD, altitude, etc. Thus, an attempt to improve the results of the estimate was made by including the cold cloud duration (CCD) in the analysis, as presented in the section that follows.

4.5. Use of CCD in kriging extrapolation

The rainfall data is under sampled as seen from the distribution of the rain gauge sites in the drainage basin. The distribution is so irregular and sparsely and non-uniformly distributed (Fig. 1). The high correlation of areal rainfall distribution with CCD is also well established phenomenon signifying the background cross-correlation between rainfall and CCD. Hence we have explored the potential use of cokriging system in rainfall interpolation in this tropical basin.

Kriging with external drift using CCD was investigated to improve the results of the estimate, the result obtained was not better than the result obtained by the ordinary kriging. However, improvements of the results were observed when the CCD was used as a background image. The technique involved creating of the ratio map of observed rainfall to the corresponding CCD image by using the ordinary kriging, this image is finally converted into the estimated rainfall by multiplying with the CCD image. To the annual rainfall data, a spherical model was fitted to semi-variograms with a range of 0.78° and 38% of nugget effect to sill

Table 4
Model efficiency of the CCD-based improved ordinary kriging model

Ordinary kriging parameters		Search radius (°)	No. of data	R^2 (%) using drift variable	
				CCD	MAR/CCD ratio
Nugget	0.24	1.0	1–20	59.3	64.5
Sill	0.63				
Range	0.78				

ratio. The results of the performance index (R^2) is given in Table 4. From Table 4, it can be noted that there is slight improvement when the ratio of MAR to CCD is used as secondary variable or external drift in interpolation of annual rainfall.

Comparison between observed and model simulated annual rainfall in the Rufiji basin using the adopted geostatistical model of ordinary Kriging with MAR/CCD ratio as secondary variable is shown in Fig. 6. The interpolated ratio surface after being converted into the actual estimated was compared with the observed mean annual rainfall values for the Rufiji basin. The improved mean annual rainfall surface image with resolution of 10 km × 10 km is given in Fig. 7.

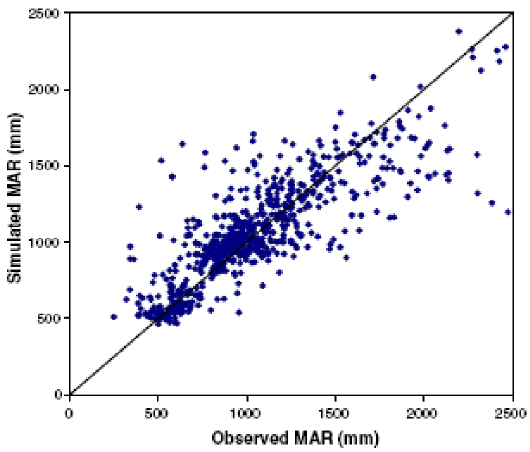

Fig. 6. Comparison between observed and model simulated annual rainfall (MAR) in the Rufiji basin.

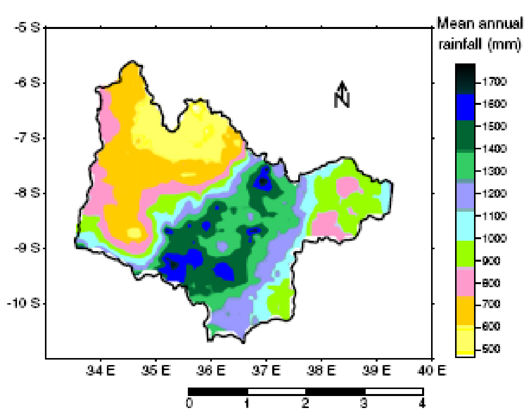

Fig. 7. Derived mean annual rainfall of the Rufiji basin using ordinary kriging using CCD as external drift.

5. Summary and conclusions

In this analysis various deterministic geostatistical techniques are investigated and implemented; simple kriging (SK), ordinary kriging (OK), kriging with trend model or external drift (KED) and cokriging (CK). The parameters obtained from the spatial continuity modelling are the basis for associating the weights to each neighbouring stations in estimating the unsampled value $Z(u)$. Investigation of various kriging algorithms reveals that, in general the ordinary kriging technique is a robust estimator on the basis of Nash and Sutcliffe efficiency criteria (R^2). Generally, OK produced reasonably better estimation result with R^2 value of 61.4% for Rufiji mean annual rainfalls.

After exhaustive modelling analysis, parameter sensitivity analysis and examination of the residual error is carried out for any indication of existence of systematic error in the estimates and to look for possible inadequacies of the assumed model structure. The parameter values, as long as they are in acceptable ranges, have been found more resistant (less sensitive) in the sense of the efficiency criterion (R^2) for any different combination of parameters.

The use of CCD image as a back ground image in estimating the rainfall quantity has proved to be very essential as the performance index (R^2) has shown improvement over the estimation based on observed rainfall alone. An attempt to improve the results of the estimation by incorporating related secondary variables such as cold cloud duration (CCD) shows little or no improvement at all for SK, OK, and CK kriging types. An encouraging improvement is obtained by including the secondary variable as a ratio to the primary variable as well as further use of the estimated surface from the MAR/CCD ratio as a drift data and kriging with external drift. Notable improvement in the model efficiency (R^2) was obtained by using ordinary kriging (OK) with external drift using the ratio of MAR/CCD as external drift. The R^2 was improved from 61.4% to 64.5%.

Over all, the spatial rainfall variation in the Rufuji basin does not depend entirely, on the parameters controlling the shape of the model variogram such as nugget effect, sill or range, etc. and it is sensitive to the type of kriging method used. In our opinion, the most important factor in the modelling of the spatial behaviour is the profound understanding of the nature of the rainfall distribution in the area, and identification of the related variables that affect rainfall occurrence and its magnitude.

The spatial behaviour of rainfall becomes notoriously variable as the time step becomes smaller. One can estimate the mean annual rainfall of an area more accurately than estimating the daily rainfall amount where as the information that can be extracted from daily rainfall is very important than the larger time steps from planning as well as operational point of view. Thus it is the recommendation of this study to further investigate the spatial variability or fluctuation of rainfall on a lesser time step such as of daily, weekly or decadal time scales by incorporating the probabilistic geostatistical methods as well as real time ground-based (observed) rainfall and CCD data.

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