Using Model Data to Build on Accuracy of Ground Data based on Kriging, Interpolation Techniques for Bias Correction

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Abstract— The estimation, with precision, of spatial patterns in rainfall from different independent sources is a challenge because of the extreme variability of rainfall in space and time. Quantification and understanding of the uncertainties associated with the spatial analysis of climate data are thus essential for efficient forecasting using interpolation techniques to estimate the spatial distribution of the precipitation. Given this variability in time and space, ground-based gauge networks may not provide a robust basis for interpolation, and the reliability of remote sensing products, although improving, is still imperfect. The technique we proposed in this paper is based on combination different kinds of measurements to correct the bias. We used model ERAI data domain 1 and 3 and model CCSM4 "The Community Climate System Model" data domain 1 and 3 to correct the ground station data (ground data corrects model). Kriging method is used for bias correction. The statistical properties of the data are used to analysis the data, simulation before the bias correction to estimation bias. And the bias has been re-evaluated after correction. The simulation result shown kriging interpolation can be used for site data interpolation for better prediction.. Daily data (ERAI "EUNIS Research and Analysis Initiative", CCMS4) for the five years (2001 to 2005) are used.

Key words: The Community Climate System Model, CCSM4, Kriging method

I. Introduction

Semi-arid West Africa is characterized by the Sahel. The Sahel zone represents a unique area where systematic, unusual, and dramatic trend in rainfall characterize the climate variability (J. Bayo Omotosho 2000,Tiganadaba L. et al 2013, Ingram et al. 2002, C Mc Sweeney et al 2006, K. Berthe et al 2015). Importantly, the zone has witnessed the most outstanding climatic shift in the late 20th century, with multi-year episodes of extreme drought (Hulme 1992. Okoro et al 2014).

Analysis the spatial distribution of rainfall is greatly hampered by the lack of sufficiently dense network (ground stations and satellite) of weather data collection stations. In climatology, spatial analyses are very useful since they ease the handling of large sets of data and they allow appreciation of a phenomenon at a broader scale. Two types of sensors are commonly used in the satellite rainfall estimation algorithms: Passive Microwave (PM) and Visible Infrared Radiance (VIS/IR). The PM sensors identify the precipitation particles by the scattering due to large ice particles present in the clouds. The sensor based-IR data relate rainfall to cloud top temperature and cloud optical properties through a precipitation index (Kidd, 2001 d1, Edert et al., 2007 , T. Cohen et al 2012).

In Most Sahel countries, the spatial ground stations data network is characterized by the scarcity, also the lack of professional data collectors, which make the use of these data for prediction un-accurate. So, these data need to be further analyzed, with some satellite data or other data obtaining through forecasting model, using an appropriate interpolation tool we will be able to get accurate prediction. Several methods of interpolation exist, -R. Suilter 2008classified these methods into three main categories: deterministic, geostatistical, and other methods. Deterministic methods create a continuous surface by only using the geometric characteristics of point observations. Probabilistic methods used the concept of randomness (Masih et al 2011, Tabios et al 1985, Lloyd, 2005, 1964). Other methods combine both deterministic and probabilistic methods (Yang, et al 1998, Rouzbeh .s et al 2009, Vazila K. et al 2012, R. Venjata et al 2013).

While some studies have analyzed the interpolation performance of both methods, most of them are over a monthly or annual period (Tabios 1985, Lastly, Goovaerts 2000, Basistha et al 2008, Moral 2010). Few of them focus on daily time scales (Beek et al 1992, Kyriakidis et al 2001 Schuurmans et al 2007). In most literatures, the performance of one method to another differs from one study to another (Lanza et al 2001, Johnson et al., 1995; Buytaert et al., 2006 , Sinclair et al., 1997, Chow et al 1988, Nicotina et al 2008, Mandapaka et al., 2009). The successful performance of the methods depends on several factors, in particular, temporal and spatial resolutions of the data, and the parameters of the models. It is difficult to draw a general conclusion. No one interpolation method stands out as being universally the best (Ruelland et al 2008, Masih 2011, Sarann Ly et al 2013).

The recent development of Geographic Information System (GIS) interpolation theory has shown the efficiency of kriging method for spatial data interpolation; natural finite element interpolation method is also an efficient tool for engineering. In this paper, we compare these two interpolation methods for bias correction. The methodology is that, three different sources (observed, CCSM4 and ERAI data) for a period of 2001 to 2005 are used to correct the gauge (ground station) data.

This paper is composed as: in the next chapter, we firstly introduce the study area and then we make spatial analysis of the data. Chapter 3 is focused on the computation of statistical parameters in order to make an efficient correction. In chapter 4 we presented the interpolation methods, and compute the un-bias values of

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the data for each point. The conclusion is presented in chapter 5.

II. SPATIAL ANALYSIS OF THE DATA

A. *Study Area*

Situated in western Africa at latitudes of 10 to 25oN, (9.8579 "i=170" to 25.2787 "i=219") longitude -12.5 to 5oW (-12.1324 "j=34" to 5.0759 "j=87"), Mali climate as well as the other Saharian countries climate is characterized by large variations, thus contributing to uncertainty in regional forecasting and prediction (Christensen et al. 2007). Globally the inter annual or the seasonal cycle variation of precipitation in Mali and most Sahel countries is a peudo-periodic in time series domain (fig 1). Like Niger, Chad the climate of Mali is mostly dominated by great mitigation of the ITCZ and the precipitation depends on the seasonal movement of the inter-tropical conversion zone (ITCZ); which oscillation between the northern and southern tropics over the course of a year (Jones et al 2005) (see fig 1).

B. *Data Presentation*

In this paper three kinds of data (table 1) for the period of 2001 to 2005 \ARE used:1) the ground stations data provide by the department of meteorology of Mali; 2) simulation data provide form ERAI (EUNIS Research and Analysis Initiative) where EUNIS mean European nature information system ", and 3) CCSM4" The Community Climate System Model" model from University of Nebraska Lincoln (department of Climate modeling).

<table>
<tr><td colspan="5">Data</td></tr>
<tr><td>Period</td><td colspan="4">2001-2005</td></tr>
<tr><td colspan="5">Type</td></tr>
<tr><td rowspan="3">Ground station</td><td colspan="4">Similate</td></tr>
<tr><td colspan="2">Domain 1</td><td colspan="2">Domain 3</td></tr>
<tr><td>ERAI</td><td>CCSM4</td><td>ERAI</td><td>CCSM4</td></tr>
</table>

Table 1: data resume, data characteristic

From table 1 the ERAI data is for domain 1 and domain 3 as well as CCSM4 data domain 1 and 3. All the computation is done based on the daily data (annual data have been computed based the cumulated daily data). Eight localities have been selected in this study (table 2); each locality has been selected according to specificity, geographic position, economical position and mainly the quality of data acquisition (professionalism, the frequency of the measurement per day). The coordinates for each point are specified in the table 2.

	Bamako	Bougouni	Hombori	Kayes	Koutiala	Mopti	Sikasso	Segou
Latitude	12	11	15	14	12.3	14	11	13
Longitude	-7.56	-7.3	-1.41	-11.26	-5.28	-4.06	-5.41	-6.09

Table 2: geographic location for each sites (latitude and longitude)

C. *Precipitation Frequency Analysis*

Fig 1 shows the distribution of precipitation for the five years for the localities of Bougouni, Bamao, Segou, Sikasso and Koutiala. From fig 1, it is clear that globally precipitation curve is periodic. One year precipitation (seasonal) is presented in fig 2.

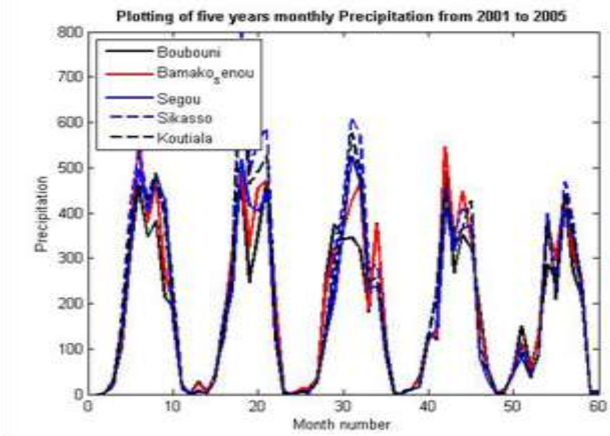

Fig. 1: represented five years ground station precipitation for Bamako-Senou, Koutiala, Bougouni, Segou , and Sikasso

From fig 2 which presents precipitation of one year (2001), we can show the partition the monthly partition of precipitation in Mali. The annual season is be sub-devise in four sub-seasons: JFM (January, February, March) with less precipitation, AMJ (April, Mai, June), and JOS (July, August, September), the precipitation period, and OND (October, November, December) with no rainfall activities.

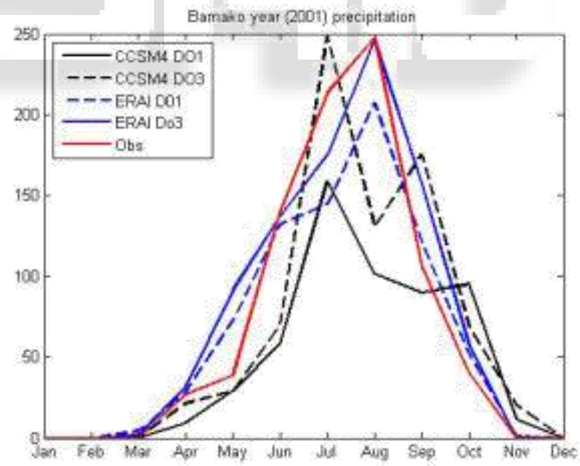

Fig. 2: Monthly precipitation for year of 2001, for Bamako-Senou: according the four data sources.

Comparison with ground station measurements showed the observe data seem to be the most accurate than models rainfall data. From fig 2 we see the trend of evolution of precipitation data for each model. The precipitation estimated by CCSM4, ERAI are all greater than the observed data from the period of March to middle of September and from mi-September to December the observed data is greater than CCSM4 and ERAI data. Domain 1 of CCMS4 data represented by continuous black color curve is the lower compare to other curves.

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D. Cumulated Precipitation Data Analysis

In this section we plot the data for each site according for parameters (ERAI, CCMS4 domain 1 and 3 and the ground observation data).

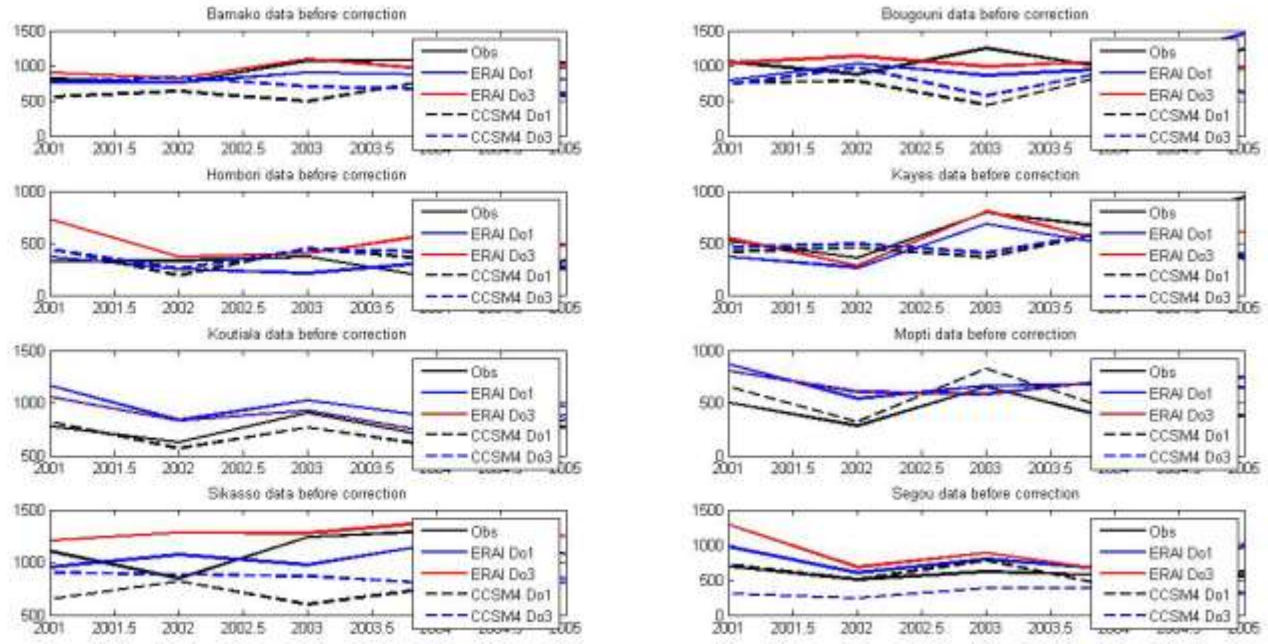

Fig. 3: shown the trend of observed data, ERAI (domain 1 and 3) CCSM4 (domain 1 and 3) before the correction for all the sites (Bamako Bougouni, Hombori, Kayes, Sikasso, Segou, Mopti and Koutiala).

In this paper we supposed the ground data to be the more realistic, so more accurate than ERAI and CCMS4 data obtaining by modeling. From fig 3 evolution of the precipitation each localities is not fitting the observed data. The different between the data is more observed for Sikasso than other sites this means the data bias. To make an accurate prediction correction is needed.

III. STATISTICAL ANALYSIS OF THE DATA

Satellite observations of rainfall have well-known limitations, including sensitivity to precipitation type (Huffman et al 2007), underestimation of orographic rainfall (Chen et al 2013, Marc et al 2013). It is recognized that the satellite data represent areal rainfall, while the gauge data represent point rainfall and that this point needs to be taken into consideration in making the comparisons (Evangelia-Maria et al 2014, Potts JM 2012). To make and compare, several parameters were calculated,including the Pearson correlation coefficient, standard deviation, Root Square Means Square (RMSE) and the Bias value.

The agreement amongthe different estimations of precipitation are studied used the correlation coefficient and the bias (Daren Harmel and Smith, 2007,T. Cohen et al 2012) to. The Pearson correlation coefficient is uses and computed as:

$$R(x,y)=\frac{\sum_{i=1}^{N}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{N}(y_i-\bar{y})^2}} \quad (1)$$

Where $x_i;\bar{x}$ are the observed precipitation and the mean of the observed precipitation $y_i;\bar{y}$ the simulated model data and it's mean respectively. The result of the simulation is presented in table 3.

correlelation		Bamako	Bougouni	Hombori	Kayes	Koutiala	Mopti	Sikasso	Segou
ERAI	**Do1**	0.850463	-0.802	-0.43766	0.581468	0.677766	0.38695	0.183916	0.676155
	Do3	0.803582	-0.945	-0.38294	0.768842	0.583517	-0.04246	0.422282	0.801181
CCSM4	Do1	-0.79908	-0.71679	0.259027	-0.39199	0.677775	0.241702	-0.57187	0.02914
	Do3	0.145728	-0.85745	-0.19742	-0.4028	0.744009	0.980617	-0.53421	0.674117

Table 3: Pearson correlation coefficients of the precipitation for the period of 2001 to 2005

To highlight the nature of the agreement between the four data and the observed data. Descriptors, the correlation matrix is determined, results, reported in Table 3 the trend of the correlation coefficient variation negative for some sites like Bougouni, Hombori this implied the contrary direction of evolution between ERAI (domain 1 domain 3) CCSM4 (domain 1 and domain 3) data comparing to the observed precipitation (ground station data). So, it is inappropriate to make an efficient conclusion about the trend of these data without correcting the bias. But the highest correlation coefficient are recorded withCCSM4 domain 3 data for the site of Mopti. The coefficient of

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correlation is also relatively good for Bamako with ERAI domain 1 (.98).

To extend the analysis, we compute the Standard deviation (STD), which is defined as the dispersion of the biased values around the mean value. It is computed uses the following formula:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n-1}} \quad (2)$$

where σ is the standard deviation and $\overline{x}$ is the sample mean . The result of the simulation of the standard deviation using equation 2 is presented in table 4.

standard deviation		Bamako	Bougouni	Hombori	Kayes	Koutiala	Mopti	Sikasso	Segou
Obs		155.2541	167.3658	79.60671	225.9308	108.7707	147.7167	175.222	71.95503
ERAI	Do1	60.97336	261.1668	61.43899	157.4334	131.7103	120.6706	126.2262	171.4828
	Do3	102.4092	70.73113	147.9406	190.579	127.0332	89.99232	64.95073	270.0195
CCSM4	Do1	121.6652	172.5234	91.1399	106.7948	130.1302	214.0535	99.34517	155.181
	Do3	121.6652	172.5234	91.1399	106.7948	130.1302	214.0535	99.34517	155.181

Table 4: standard deviation evolution during the period of five years of precipitation

In practice, a low standard deviation indicates that the data points tend to be very close to the mean; which is observed for ERAI domain 1 for Bamako, ERAI domain 3 for Bougouni; ERAI domain 1 for Hombori etc. The high standard deviation indicates that the data points are spread out over a large range of values which is observed for ground station for Kayes (225.9308), ERAI. Domain 1 data for Bougouni (261.1668) and Segou ERAI domain 3(270.0195).

Root Mean square Error (RMSE) is a frequently used measure of the difference between values predicted by a model and the values actually observed. The RMSE uses the following formula:

$$RMSE = \sqrt{\sigma^2 + \overline{x}^2} \quad (3)$$

where $\overline{x}$ is the sample mean and σ is the standard deviation.

The biasbetween the observed data and the model data is computed used Eq (4). The result of simulation is presented in table 5. The bias shows the predominance of observed data if it is positive and model data (ERAI, CCSM4) if it is negative. The bias is calculated used the following formula:

$$Bias = \frac{\frac{1}{N}\sum_{i=1}^{n}(O_i - F_i)}{\sum_{i=1}^{n} O_i} \quad (4)$$

Where O_i is the gauged data (ground observed data), and F_i the model data (ERAI or CCSM4). The simulation data is represented in table 4.

Bias		Bamako	Bougouni	Hombori	Kayes	Koutiala	Mopti	Sikasso	Segou
ERAI	Do1	-0.03418	-0.04676	-0.01503	-0.08198	0.074381	0.152562	-0.02505	0.089466
	Do3	0.001349	0.008369	-0.17428	0.040288	-0.04427	-0.13702	-0.03718	-0.13259
CCSM4	Do2	-0.00395	-0.01133	0.04282	-0.00251	0.007309	0.022629	0.000736	0.00511
	Do3	-0.08991	-0.08787	0.051944	-0.0813	-0.01087	0.049807	-0.08667	0.007028

Table 5: bias data for the five years precipitation trend

From table 4 we can see the trend of the bias; most values are negative this means the value of model data are greater than observed data which is the over-estimation of the gauge data. The value of the bias is maximum for Hombori with the ERAI domain 3 data (-0.17428). We can conclude from table 4 the model data are near the observed data, because the bias is small (less than 18%).

IV. Interpolation

A. Introduction

As mentioned in the introduction several interpolation methods exist. The general formula for spatial interpolation as:

$$Z_g = \sum_{i=1}^{ns} \lambda_i Z_{s_i} \quad (5)$$

where Z_g is the interpolated value at the required points, Z_{s_i} is the observed value at point i, ns is the total observed value at points and $\lambda = (\lambda_i)$. It is the weight contributing to the interpolation.

The problem lies in calculating the weights, λ which will be used in the interpolation. The different methods for computing the weights determine the type of interpolation include:

B. Kriging Technique

Kriging method is mostly used for spatial precipitation interpolation. Our methodology isto merge with the gauged (observed data) and the data obtained from models (ERAI, CCMS4) on the same grid (blocks). In this paper, standardized ordinary co-kriging (Isaaks and Srivastava

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1989, Evangelia-Maria et al 2014) is used to calculate the merged precipitation $\hat{Z}_A(u_A)$ from a linear combination of gauge and model data. At point u_A we used the following formula:

$$\hat{Z}_A(u_A) = \lambda_{G_A} Z_G(u_A) + \lambda_{S_A}(Z_S(u_A) - \hat{m}_{S_A} + \hat{m}_{G_A}) \quad (6)$$

This approach uses only nonbiased conditions, namely $\lambda_{G_A} + \lambda_{S_A} = 1$, which requires the adjustment of the model estimates in Eq (6) to make sure that their mean is equal to the mean of the gauge values. The means of the gauge values $\hat{m}_{G_A}$ and model values $\hat{m}_{S_A}$ are computed simply as arithmetic averages. The values of the λ_{G_A}, λ_{S_A} are computed using the standard deviation as the following:

$$\lambda_{G_A} = \frac{\sigma^2_{G_A}}{\sigma^2_{G_A} + \sigma^2_{S_A}} \text{ and } \lambda_{S_A} = \frac{\sigma^2_{S_A}}{\sigma^2_{G_A} + \sigma^2_{S_A}}$$

V. SIMULATION AND DISCUSSION

In order to compare the two methods, the bias value is computed after correction (interpolation) the following formula is:

$$Bias = \frac{\frac{1}{N}\sum_{i=1}^{n}(O_i - E_i)}{\sum_{i=1}^{n} O_i} \quad (8)$$

Where E_i is the estimated observed value after interpolation. The result of the simulation is presented in table 5.

Corected Bias		Bamako	Bougouni	Hombori	Kayes	Koutiala	Mopti	Sikasso	Segou
ERAI	do1	0.014462	0.023135	0.014927	0.079923	0.059596	0.092593	0.027822	0.055363
	do3	0.012211	0.003738	0.099068	0.010655	0.044327	0.084101	0.016725	0.073533
CCSM4	do1	0.095443	0.097576	0.046331	0.057383	0.000328	0.040927	0.121165	0.006007
	do3	4.26E-05	0.011652	0.013775	0.010663	0.003342	0.009793	0.039785	0.129203

Table 5: bias data after correction

Form table 5 based on equation 4, we can conclude the predominance (positive value of the bias). Comparing to table 4 (bias before correction) all values of bias before correction are absolutely greater the bias value after correction. The potting fig 5 shows the trend between estimated (corrected use kriging technique) data and the observed data.

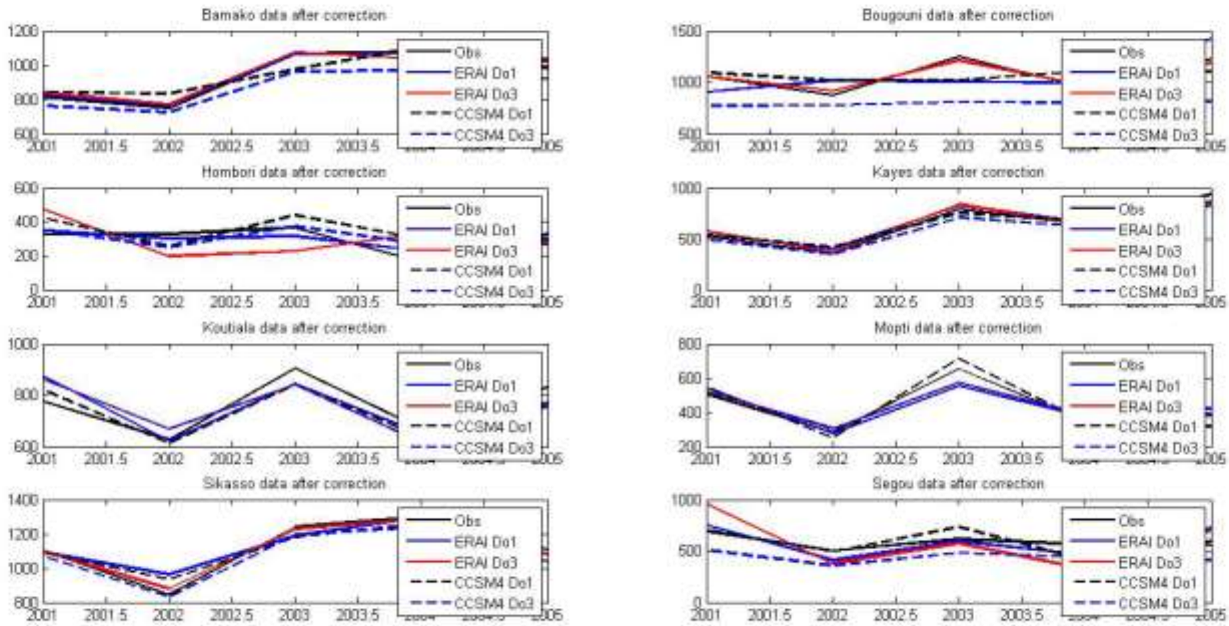

Fig. 4: corrected data compare to the observed data

From fig 4 compare to fig 3 the estimate data best fit observe data, which have been confirm comparing the bias table (table 5 and 6). We can conclude from fig 4 the bias correction is not dependant on the domain or on the model, for the site of Hombori and Bougouni the bias need to be corrected compare to the other sites.This inability needs further investigation and is the subject of ongoing research by combining other interpolation methods with Kriging technique.

This approach confirm some authors recommendation a particular method as being the best according to their judgment as to what is the most practical (Tabios et al., 1985, Abtew et al., 1993; Syed et al 2003, Okoro U.K 2014). Last Sentence Not Clear

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VI. CONCLUSION

The choice of interpolation method depends on the quality of valid measures, the nature of the parameter in the regions under study and the quality of the observations. The World Meteorological Organization (WMO) Solid Precipitation Measurement Inter-comparison (Goodison et al 1998 ,Younlong Xia et al 2006] has evaluated the relative biases of standard precipitation gauges using an extremely rigorous method (Yang et al 1998a). Their adjustments probably overestimate precipitation for gauges with Alter shields and underestimate precipitation for other gauges (Adam and Lettenmaier, 2003), leading to areal mean biases of unknown sign and magnitude. To overcome this problem, in this study we propose Kriging interpolation technique. The coefficients of interpolation are calculated based on the standard deviation. Compare fig 3 and fig 4 “the bias before and after correction”, we can conclude that efficiency of the proposed method.

A key contribution of the proposed procedure lies in its ability to improve the accuracy of observed data for prediction by combine the data from other model. The interpolation proposed provides a ground true estimate of year cumulated data and can be extended to monthly and daily rainfall distribution.

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