Statistical Downscaling Output GCM Modeling with Continuum Regression and Pre-Processing PCA Approach

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***Abstract*—One of the climate models used to predict the climatic conditions is Global Circulation Models (GCM). GCM is a computer-based model that consists of different equations. It uses numerical and deterministic equation which follows the physics rules. GCM is a main tool to predict climate and weather, also it uses as primary information source to review the climate change effect. Statistical Downscaling (SD) technique is used to bridge the large-scale GCM with a small scale (the study area). GCM data is spatial and temporal data most likely to occur where the spatial correlation between different data on the grid in a single domain. Multicollinearity problems require the need for pre-processing of variable data X. Continuum Regression (CR) and pre-processing with Principal Component Analysis (PCA) methods is an alternative to SD modelling. CR is one method which was developed by Stone and Brooks (1990). This method is a generalization from Ordinary Least Square (OLS), Principal Component Regression (PCR) and Partial Least Square method (PLS) methods, used to overcome multicollinearity problems. Data processing for the station in Ambon, Pontianak, Losarang, Indramayu and Yuntinyuat show that the RMSEP values and $R^2_{predict}$ in the domain 8x8 and 12x12 by uses CR method produces results better than by PCR and PLS.**

Keywords—**CR, PCA, PCR, PLS, SD, GCM**

I. INTRODUCTION

Recently General Circulation Models (GCM) is recognized by many people as important tools in understanding the climate system. But many scientific communities expressed some dissatisfaction, because it has produced an inadequate space scale forecast [14]. One effort to overcome these problems is the use of Statistical Downscaling (SD) method [4]. The main advantage of this method is inexpensive computation and easy application in many output simulations and experiments which based on GCM.

Some SD methods for many climate studies were developed in high latitude countries, whereas in low latitude region (such as Indonesia) is still very limited [4][14].There are SD methods for generating large scale and local scale model relathionship such as based on region or spatial, temporal, dependent variable, independen variable, and statistical methods. SD method often used are classical or multiple regression [1, 2], canonical correlation [2, 16], Singular Value Decomposition (SVD) [11], and non linear approach such as artificial neural network [3]. SD models developed in Indonesia are Haryoko (2004) and Wigena & Aunuddin (2004) [13], but it did not consider spatial however correlation, autocorrelation case and problems of non linear structure data.

The problems that arise in the SD method are how to determine domain (grid) and dimensions reduction, how to obtain an independent variable that may explain the diversity of the dependent variable, and obtain appropriate statistical methods of data characteristics that can describe the relationship between independent variables and the dependent variable, accommodate how to employ extreme events. The method often used for pre-processing are the Principal Component Analysis (PCA), Discrete Wavelet Transform (TWD), Robust Principal Component Analysis (ROBPCA), and Kernel PCA; furthermore, Continuum Regression (CR) is also a model for the dependent variable with variable pre-processing. It is one potential method to overcome the multicollinearity.

The purpose of this study is to compare the performance of CR, PCR and PLS with PCA pre-processing by Root Mean Square Error Prediction (RMSEP) and R^2_{predict} criteria.

II. THEORIES

A. Principal Components Analysis (PCA)

PCA is a procedure to reduce the dimension of data by transforming the original variables correlated to a set of new uncorrelated variables. New variables are told as a Principal Component (PC) [6].

PC can be obtained from the eigenvalue-eigenvector pairs of covariance matrix or correlation matrix. First, standardization of data is done first when a unit of data between variables are not equal. It isessensially done so that the dominance of one or two variables in a PC can be avoided. If Σ is a variance-covariance matrix from random vector $X^T=[X_1,X_2,\ldots, X_p]$. Σ is obtained from the method of Maximum Likelihood Estimation (MLE) with the formula in Equation (1).

$$\boldsymbol{\Sigma} = \frac{1}{n-1}\sum_{i=1}^{n}(x_i-\boldsymbol{\mu})(x_i-\boldsymbol{\mu})^T \quad (1)$$

$$\boldsymbol{\mu} = \frac{1}{n}\sum_{i=1}^{n}x_i \quad (2)$$

$$Z_2=\mathbf{e}_2^T\mathbf{X}= e_{12}X_1 + e_{22}X_2 + \ldots + e_{p2}X_p$$

....

$$Z_p=\mathbf{e}_p^T\mathbf{X} = e_{1p}X_1 + e_{2p}X_2 + \ldots + e_{pp}X_p \quad (3)$$

with:

Z_1 = first PC, which has the largest variance

Z_2 = second PC, which has the second largest variance

Z_p = *p*-th PC, which has *p*-th largest variance

X_1 = the origin of the first variable

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X_2 = the origin of the second variable
X_p = the origin of the *p*-th variable
PC models *i*-th can also be written with the notation $Z_i = e_i^T X$ where,
i = 1, …,p and:

$$Var(Z_i)=e_i^T\Sigma e_i,\ i=1,2,...,\ p \quad (4)$$

$$Cov(Z_i, Z_k) = e_i^T \sum e_k,\ i \neq k \quad (5)$$

PC are not correlated and have the same variance with eigenvalues of Σ, then,

$$\sigma_{11}+\sigma_{22}+...+\sigma_{pp} = \sum_{i=1}^{p} \mathrm{Var}(X_i) = \mathrm{tr}(\Sigma) = \lambda_1+\lambda_2+...+\lambda_p \quad (6)$$

when the total population variance is,
$\sigma_{11}+\sigma_{22}+\sigma_{pp}=\lambda_1+\lambda_2+\ \dots+\lambda_p,$ then,
total variance can be explained by the i-th PC

$$= \frac{\lambda_i}{\lambda_1+\lambda_2+...+\lambda_p} \quad (7)$$

if the PC is taken as *k*, where (*k*<*p*), then,

$$= \frac{\lambda_1+\lambda_2+...+\lambda_k}{\lambda_1+\lambda_2+...+\lambda_p} \quad (8)$$

Furthermore, when it is employed used the beginning is the covariance matrix of standardized data, due to the main diagonal matrix containing the value of one, then the total population variance for the standardized variable is p, representing the diagonal matrix elements ρ,then total variance can be explained by the *i*-th PC

$$= \frac{\lambda_i}{p} \quad (9)$$

B. Partial Least Square (PLS)

PLS method is a statistical method to generalize and combine the methods of factor analysis, PCA, and multiple regressions. The purpose of PLS is to form a component that can capture information from the independent variable to predict the dependent variable.

PCA focuses on diversity in the independent variables, while PLS focuses on the covariance between independent variables and the dependent variable. The model from PLS methods consists of external and internal relations. External relations in the PLS is an individual and group relationships.

C. Continuum Regression (CR)

CR is a regularized regression estimation methods (a set), and used to handle the collinearity or multicollinearity problems, which means there are approaches a linear relationship between the independent variables. CR is developed from the OLS, PCR, and PLS regression.

Based on the following linear regression model:

$$\mathbf{y} = X\beta + \varepsilon \quad (10)$$

with independent variable X (size nxp) that has been centered and the dependent variable **y** (size nx1) is the vector that has been centered. In the case of multicollinearity show that X is not full rank matrix. Consequently, matrix X^TX is (almost) singular.

In a linear weighted regression model, mathematical formula can be written as follows, by maximizing

$$= r_w^2 = \frac{\left(\sum_{i=1}^{n} y_i \mathbf{w}^T \mathbf{x}_i\right)^2}{\left(\sum_{i=1}^{n} y_i^2\right)\sum_{i=1}^{n} (\mathbf{w}^T \mathbf{x}_i)^2} = \frac{(\mathbf{w}^T \mathbf{s})^2}{\|\mathbf{y}\|^2\, \mathbf{w}^T \mathbf{S}\mathbf{w}} \quad (11)$$

With $\mathbf{x}_i$ is the observation vector with the i-th independent variables (i=1,2, ..., n) size (px1),s = X^Tyand S = X^TX.

PCR principle is to maximize:

$$S_w = \sum_{i=1}^{n} \left(\mathbf{w}^T \mathbf{x}_i\right)^2 = \mathbf{w}^T \mathbf{S}\mathbf{w} \quad (12)$$

From formula (12) shows that the basic principle of PCR is used to maximize the variance of the independent variable X thus a new variable is formed in the form of several major components which are linear combinations of original variables (X). Furthermore, the dependent variable y is regressed with several major components using multiple linear regression techniques.

PLS regression principleis to maximize :

$$S_w = \left(\sum_{i=1}^{n} y_i \mathbf{w}^T \mathbf{x}_i\right)^2 = \left(\mathbf{w}^T \mathbf{s}\right)^2 \quad (13)$$

Then from formula (13) it can be seen that PLS regression principle is used to maximize the covariance between the dependent and independent variables.

New variable in CR are written as follows in Equation (14).

$$y = T_h\xi + \varepsilon, \text{ with } T_h = XW \quad (14)$$

And W_h = ($w_1, w_2, \dots, w_h$) is a matrix containing h columns variable with h < p and called as weighting matrix.

Stone and Brooks (1990) formulated the following weighting matrix as [4]:

$$w_i = \arg w_{max}\{Cov(X_w, y)^2 Var(X_w)^{[\delta/(1-\delta)]^{-1}}\} \quad (15)$$

with constrains$\|W_2\|$=1 and Cov(Xw_i, Xw_j) = 0 for i < j while the parameter adjustment δ is a real number 0 ≤ δ ≤1.

Another alternative is a formula developed by Malpass (1996) as follows [7] :

$$w_i = \arg w_{max}\{Cov(X_w, y)^{(2+2\delta-4\delta^2)} Var(X_w)^{(-1+2\delta)}\} \quad (16)$$

From the formula (15) made a general formula as follows:

$$G = \left(w^T X^T y\right)^2 \left(w^T X^T X w\right)^{[(\delta/(1-\delta))-1]} \quad (17)$$

Furthermore it was called as Stone methods. From the formula (16) can be made into :

$$G = \left(w^T X^T y\right)^{(2+2\delta-4\delta^2)} \left(w^T X^T X w\right)^{(-1+2\delta)} \quad (18)$$

Furthermore this formula was called the Portsmouth methods [7].

The formula is a generalization of the OLS, PCR and PLS with the following forms of linkage:

1. For δ = 0, then G = $(w^Ts)^2(w^TSw)^{-1}$ this formula is equivalent to Equation (11), thats mean, if δ = 0 CR is OLS.
2. Forδ = 0.5, thenG = $(w^Ts)^2$ this formula is equivalent to Equation (12), so that, if δ = 0.5CR is PLS
3. Forδ = 1, thenG = (w^TSw) this formula is equivalent to Equation (13), so that, if δ = 1 CR is PCR.In other words, OLS, PCR and PLS are a special form of CR.

Estimation of regression parametersξ in the Equation (14) performed using least squares method is formulated as follows:

$$\hat{\xi}_{\delta,h} = \left(\mathbf{T}_h^T \mathbf{T}_h\right)^{-1} \mathbf{T}_h^T \mathbf{y} \quad (19)$$

$$\hat{y}_{\delta,h} = XW_h\hat{\xi}_{\delta,h}$$

$$\hat{\beta}_{\delta,h} = W_h\left(T_h^T T_h\right)^{-1} T_h^T y \quad (20)$$

where δ is an adjustment parameters and h is the number of components.

D. Goodness Model

Common measuring using good us model has the coefficient of determination R^2 describing the goodness of prediction.

$$R^2_{predict} = 1 - \frac{SS_{Error}}{SS_{Total}} = \frac{\sum_{i=1}^{n} (\hat{Y}_i - \overline{Y})^2}{\sum_{i=1}^{n} (Y_i - \overline{Y})^2} \quad (21)$$

$R^2_{predict}$ = coefficient determination
$\bar{Y}$ = mean of the observed data
Y_i = actual values
$\hat{Y}$ = prediction values
Another criteria is :

$$RMSEP = \sqrt{\frac{\sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2}{n}} \quad (22)$$

RMSEP = Root Mean Square Error Prediction
n = number of sample
Y_i = actual values of out sample data
$\hat{Y}$ = prediction values of out sample data

E. General Circulation Model (GCM)

GCM is climate models based on computer. It uses numerical and deterministic equations which follow the physics rules. GCM is the main tool to predict or forecast climate and weather, understanding climate and climate change studies. According to [15], GCM is a major tool in the study of diversity and climate change. GCM climate models have the form of outcome-grid grid size 100-500 km, according to the latitude and longitude. This model can be used to predict changes in weather elements [16]. However, GCM is a global information, so it is difficult to obtain direct information on the local scale. But the GCM is still possible to obtain information about local or regional scale when the downscaling technique is used [13].

Downscaling is defined as an effort to connect between global-scale circulation variables (explanatory variables) and local scale variables (dependent variable) [9]. To bridge the large-scale GCM with a smaller scale (the study area), it use SD. SD is a process of downscaling which static, data on large-scale grid-grid in a certain time period and used as the basis for determining the data on a smaller scale grid [13].

SD approach uses regional or global data to obtain the functional relationship between the local scaleto global scale GCM. In general, the relationship is expressed by:
$Y = f(Z) + \varepsilon$
with,
Y :dependent variable (rainfall)
Z :independent variable (compound of the reduction result of spatial (latitude and longitude) GCM variables
ε : error

III. METHOD

This research uses secondary data obtained from GCM output model CSIRO-Mk3, resolution of grid latitude and longitude 1,8650 x 1,8750. It can be downloaded at http://www-pcmdi.llnl.gov/ipcc. GCM domains are 3x3, 8x8 and 12x12 from five stations. Pontianak station uses the datafrom 1947-1990. Ambon Station use data in 1900-1940, Losarang Station in 1967-2000, Indramayu Station in 1974-2000, and Yuntinyuat Station in 1974-2000. Monthly rainfall data are obtained from *Badan Meteorologi Klimatologi dan Geofisika (BMKG)*.

Independent variables are CSIRO Mk3 outcomes. They are precipitable water (PRW), sea level pressure (SLP), meridional wind component (VA), zonal component (UA), geopotential height (ZG), and specific humidity (HUSS). The height (level) is 850 hPa, 500 hPa and 200 hPa. The dependent variable is the monthly rainfall data from five stations.

There two criteria to get the performance of CR, PCR and PLS with PCA dimension reduction, namely: RMSEP and $R^2_{predict}$. The best model is the model with small RMSEP and high $R^2_{predict}$.

IV. RESULT AND DISCUSSION

A. Pre-processing SD Modeling

The first step in the SD modeling is by means of dimension reduction, called the pre-processing of data. Spatial dimension reduction is performed on the latitude and longitude or grid and called on all variables in every level and every domain. In this case, each grid is an independent variable, so the domain 3x3, 8x8 and 12x12 are respectively sequenced 9, 64, and 144 variables and they will be reduced.

B. PCA Method

The procedure for preparing the main components with the PCA is done through three steps: first, getting the variance-covariance matrix, second, obtaining eigenvalues and eigenvector matrix of variance-covariance based on the first step, and finally conducting a linear combination of eigenvector with the origin data to obtain the main components.

Through the steps using the PCA method, it is obtained the number of principal components and cumulative variance (CV) for GCM variables, listed in Table 1 until Table 3.

Based on Table 1 the components produced by GCM variables using the PCA method have CV greater than or equal to 85%. Domain 3x3 is using one main component, except for variable HUSS. HUSS variable use three main components, which subsequently written HUSS1, HUSS2, and HUSS3. Domain 8x8 have main component which ranges from one to three, except HUSS variable that uses six main components (HUSS1, HUSS2, HUSS3, HUSS4, HUSS5, and HUSS6). Domain 12x12 has not more than four main components, except for variable HUSS and VA500.

In general, the variables on the level surface have main components which are comparable to increasing domain size, except for SLP variable.

SLP only has one until two main components. In ZG variable, expanded domain did not affect the number of main components used. Results for Ambon and Pon tianak station can be seen in Table 2 and Table 3.

C. CR, PCR, and PLS Method

SD modeling by means of CR, PCR and PLS methods uses independent variable produced from dimension reduction in PCA method. It was done in Ambon station (type local rain), Pontianak station (type equatorial rain), and Losarang, Indramayu, and Yuntinyuat station (type of monsoon rains). Ambon has total of independent variables used in the domain 3x3 are 16 variables, in the domain 8x8 are 28 variables, and in the domain 12x12 are 39 variables. Pontianak has total of independent variables used in the domain 3x3 are 20 variables, in the domain 8x8 are 40 variables and in the domain 12x12 are 53 variables.

Losarang, Indramayu, and Yuntinyuat have total independent variables used in the domain 3x3 are 19 variables, in the domain 8x8 are 34 variables and in the domain 12x12 are 50 variables. The comparison of actual values and prediction value of rainfall variable each station and each grid is shown in Table 4 - Table 8. It also can be seen in Fig. 1 – Fig. 5. Indramayu has better results than other stations. The prediction and actual value have relatively small difference. But in other stations, the comparison has not been satisfactory, because the prediction value is still far from the actual value.

RMSEP values and $R^2_{predict}$ from SD modeling use Continuum Regression method, PCR, and PLS in Ambon, Pontianak, Losarang, Indramayu and Yuntinyuat Station with domains 3x3, 8x8 and 12x12 as seen in Table 9. In domain 3x3, PLS method has RMSEP smaller and $R^2_{predict}$ higher than CR and PCR method. In domain 8x8, PLS method has RMSEP smaller and CR method has $R^2_{predict}$ higher than others. In domain 12x12, CR method has RMSEP smaller and $R^2_{predict}$ higher than others. So, it can be concluded that CR method has good performance than PCR and PLS method.

IV. CONCLUSION

CR with PCA pre-processing can be used to overcome multicollinearity problems at SD modeling to forecast the monthly rainfall in Ambon, Pontianak, Losarang, Indramayu and Yuntinyuat Station on grid 3x3, 8x8, and 12x12.

CR method show better results method of PCR and PLS Regression. It can be seen from the average value of RMSEP and $R^2_{predict}$ on each method and each grid.

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TABLE 1.
TOTAL PC OPTIMAL AND CUMULATIVE VARIANCE (CV) FROM OUTCOME VARIABLES OF GCM BY USING PCA METHOD

No.	Variable	Domain 3x3		Domain 8x8		Domain 12x12	
		PC	CV	PC	CV	PC	CV
1	HUSS	3	0.898	6	0.853	10	0.854
2	HUS200	1	0.977	1	0.864	2	0.917
3	HUS500	1	0.967	2	0.926	2	0.856
4	HUS850	1	0.937	2	0.903	3	0.884
5	PRW	1	0.923	2	0.876	3	0.899
6	SLP	1	0.975	1	0.880	2	0.959
7	UAS	1	0.949	2	0.916	3	0.875
8	UA200	1	0.985	1	0.911	2	0.973
9	UA500	1	0.918	2	0.887		0.903
10	UA850	1	0.983	1	0.859	2	0.858
11	VAS	1	0.881	3	0.881	4	0.855
12	VA200	1	0.976	2	0.941	2	0.881
13	VA500	1	0.918	3	0.897	5	0.878
14	VA850	1	0.851	3	0.915	4	0.854
15	ZG200	1	0.996	1	0.949	1	0.889
16	ZG500	1	0.997	1	0.964	1	0.899
17	ZG850	1	0.991	1	0.936	1	0.900

Processed by SAS software

TABLE 2.
TOTAL PC OPTIMAL AND CUMULATIVE VARIANCE (CV) FROM OUTCOME VARIABLES OF GCM BY USING PCA METHOD IN AMBON

No.	Variable	Domain 3x3		Domain 8x8		Domain 12x12	
		PC	CV	PC	CV	PC	CV
1	HUSS	1	0.965	3	0.866	4	0.857
2	HUS200	1	0.964	1	0.874	2	0.926
3	HUS500	1	0.952	2	0.920	3	0.928
4	HUS850	1	0.914	2	0.935	2	0.864
5	PRW	1	0.951	2	0.930	2	0.857
6	SLP	1	0.982	1	0.921	1	0.866
7	UA200	1	0.983	1	0.897	2	0.941
8	UA500	1	0.939	2	0.877	3	0.910
9	UA850	1	0.950	2	0.952	2	0.871
10	VAS	1	0.956	2	0.877	3	0.860
11	VA200	1	0.985	1	0.891	2	0.914
12	VA500	1	0.913	3	0.878	5	0.877
13	VA850	1	0.897	3	0.875	5	0.891
14	ZG200	1	0.996	1	0.970	1	0.933
15	ZG500	1	0.994	1	0.963	1	0.915
16	ZG850	1	0.979	1	0.926	1	0.884

Processed by SAS software

TABLE 3.
TOTAL PC OPTIMAL AND VARIANCE CUMULATIVE FROM OUTCOME VARIABLES OF GCM BY USING PCA METHOD IN PONTIANAK

No.	Variable	Domain 3x3		Domain 8x8		Domain 12x12	
		PC	CV	PC	CV	PC	CV
1	HUSS	2	0.872	14	0.863	16	0.860
2	HUS200	1	0.968	2	0.932	2	0.875
3	HUS500	1	0.898	2	0.921	3	0.924
4	HUS850	1	0.886	2	0.858	3	0.882
5	PRW	2	0.947	2	0.875	3	0.904
6	SLP	1	0.980	1	0.862	1	0.933
7	UA200	1	0.976	1	0.859	2	0.961
8	UA500	1	0.934	2	0.920	3	0.879
9	UA850	2	0.994	2	0.956	2	0.917
10	VAS	1	0.948	2	0.853	3	0.873
11	VA200	1	0.990	1	0.935	1	0.864
12	VA500	2	0.939	3	0.870	5	0.866
13	VA850	1	0.955	3	0.930	4	0.875
14	ZG200	1	0.999	1	0.985	1	0.951
15	ZG500	1	0.999	1	0.990	1	0.970
16	ZG850	1	0.997	1	0.943	2	0.954

Processed by SAS software

TABLE 4.
COMPARISON OF ACTUAL VALUES WITH PREDICTION VALUES AT EACH GRID STATION IN AMBON IN 1940 WITH CR, PCR AND PLSMETHODS

Month	Actual value	Domain 3x3			Domain 8x8			Domain 12x12		
		Prediction CR	Prediction PCR	Prediction PLS	Prediction CR	Prediction PCR	Prediction PLS	Prediction CR	Prediction PCR	Prediction PLS
January	140	190	240	203	104	60	149	132	37	91
February	91	96	88	61	169	118	127	179	143	144
March	168	106	153	76	271	232	228	94	197	117
April	172	167	174	197	394	258	362	342	338	352
May	1068	523	470	524	622	608	594	595	612	588
June	404	523	463	510	657	685	691	680	677	672
July	125	613	579	585	585	555	549	523	523	541
August	152	466	456	486	501	471	507	526	499	518
September	47	176	176	184	227	186	207	275	274	326
October	72	127	99	130	121	35	62	115	96	134
November	11	149	147	150	115	94	131	210	137	213
December	30	215	233	203	187	227	185	103	117	103

Processed by SAS software

TABLE 5.
COMPARISON OF ACTUAL VALUES WITH PREDICTION VALUES AT EACH GRID STATION IN PONTIANAK IN 1990 WITH CR, PCR AND PLS METHODS

Month	Actual value	3x3			8x8			12x12		
		Prediction CR	Prediction PCR	Prediction PLS	Prediction CR	Prediction PCR	Prediction PLS	Prediction CR	Prediction PCR	Prediction PLS
January	114	260	255	244	277	313	295	269	271	282
February	330	262	263	229	204	235	241	227	241	221
March	170	279	273	266	260	264	257	166	262	150
April	290	286	261	280	295	294	296	304	276	296
May	250	303	272	286	302	285	297	318	331	287
June	174	229	232	217	206	209	208	214	231	210
July	248	208	199	193	180	184	189	181	223	200
August	73	261	271	239	225	227	258	264	271	255
September	361	279	309	259	220	257	272	265	282	268
October	372	305	317	307	301	294	309	325	330	322
November	451	301	285	304	384	343	383	421	358	397
December	457	366	364	349	410	438	409	371	358	387

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TABLE 6.
COMPARISON OF ACTUAL VALUES WITH PREDICTION VALUES AT EACH GRID STATION IN LOSARANG IN 2000 WITH CR, PCR AND PLS METHODS

Month	Actual value	3x3			8x8			12x12		
		Prediction CR	Prediction PCR	Prediction PLS	Prediction CR	Prediction PCR	Prediction PLS	Prediction CR	Prediction PCR	Prediction PLS
January	397	228	245	240	407	234	255	213	200	208
February	59	269	274	279	426	262	282	268	267	291
March	81	163	182	173	104	135	126	141	92	125
April	115	147	131	147	254	185	193	140	157	208
May	93	77	83	76	171	121	104	33	47	60
June	139	54	56	57	0	0	0	16	4	0
July	12	50	52	53	0	33	0	0	0	0
August	0	45	40	48	0	32	31	35	13	24
September	10	55	65	57	24	31	16	1	0	0
October	29	62	68	64	56	48	50	94	71	49
November	220	154	133	148	293	174	177	173	154	154
December	140	187	189	184	348	206	214	203	179	194

Processed by SAS software

TABLE 7.
COMPARISON OF ACTUAL VALUES WITH PREDICTION VALUES AT EACH GRID STATION IN YUNTINYUAT IN 2000 WITH CR, PCR AND PLS METHODS

Month	Actual Value	3x3			8x8			12x12		
		Prediction CR	Prediction PCR	Prediction PLS	Prediction CR	Prediction PCR	Prediction PLS	Prediction CR	Prediction PCR	Prediction PLS
January	411	224	222	225	260	223	258	263	197	217
February	64	297	297	296	273	236	263	329	323	302
March	44	173	162	175	193	167	197	134	82	107
April	140	150	155	148	144	200	160	158	168	169
May	42	126	128	125	103	144	121	112	104	140
June	261	95	101	94	36	4	8	9	18	0
July	25	64	65	63	38	36	36	7	60	0
August	3	42	41	42	44	34	31	27	28	21
September	28	69	74	68	84	43	84	66	32	58
October	8	58	61	57	53	52	45	47	74	35
November	73	116	120	114	126	138	127	120	134	156
December	60	166	167	165	179	181	184	110	132	121

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TABLE 8.
COMPARISON OF ACTUAL VALUES WITH PREDICTION VALUES AT EACH GRID STATION IN INDRAMAYU IN 2000 WITH CR, PCR AND PLS METHODS

Month	Actual value	3x3			8x8			12x12		
		Prediction CR	Prediction PCR	Prediction PLS	Prediction CR	Prediction PCR	Prediction PLS	Prediction CR	Prediction PCR	Prediction PLS
January	611	272	302	285	410	301	309	308	282	291
February	98	319	358	327	315	330	312	298	349	361
March	82	181	184	192	135	64	92	102	13	54
April	131	141	96	138	108	197	180	176	179	181
May	67	83	83	83	11	139	111	88	92	91
June	39	74	65	74	0	0	0	0	0	0
July	9	62	49	64	0	54	0	33	3	0
August	3	43	40	47	0	39	37	63	19	34
September	29	57	69	59	0	9	0	52	10	0
October	16	55	61	61	0	59	29	40	90	27
November	150	141	84	137	122	187	157	159	153	162
December	289	205	183	205	277	277	290	300	223	287

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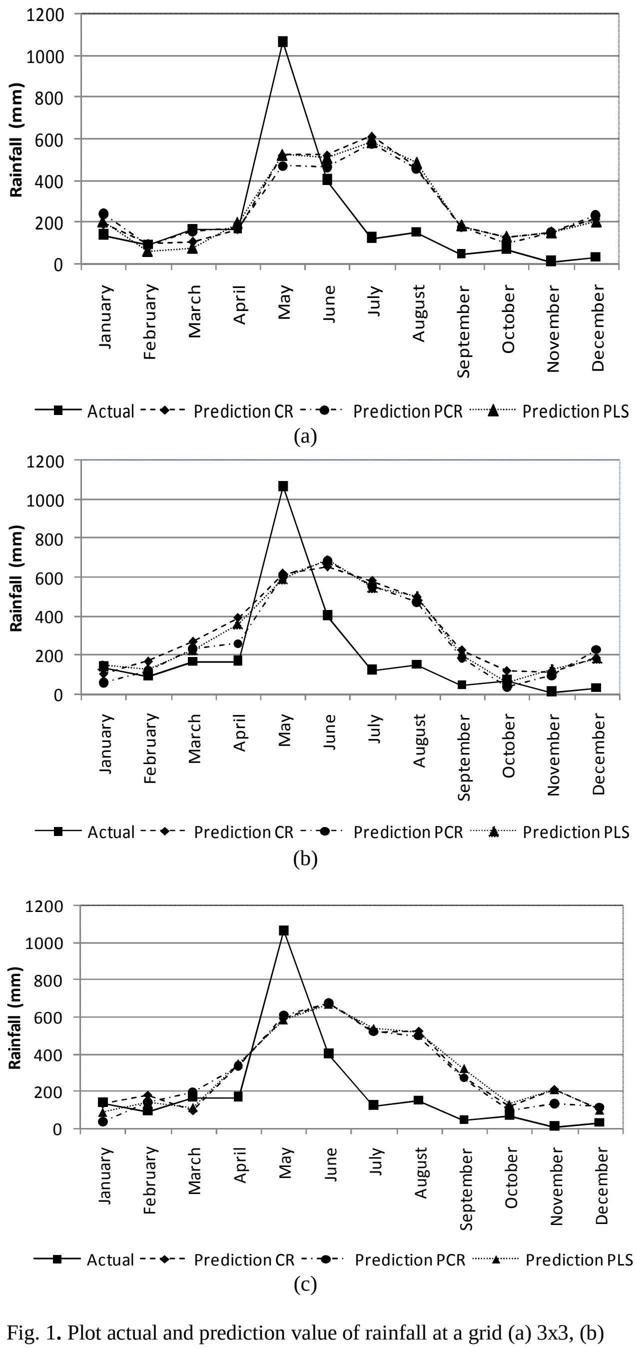


Fig. 1. Plot actual and prediction value of rainfall at a grid (a) 3x3, (b) 8x8, and (c) 12x12 in Ambon

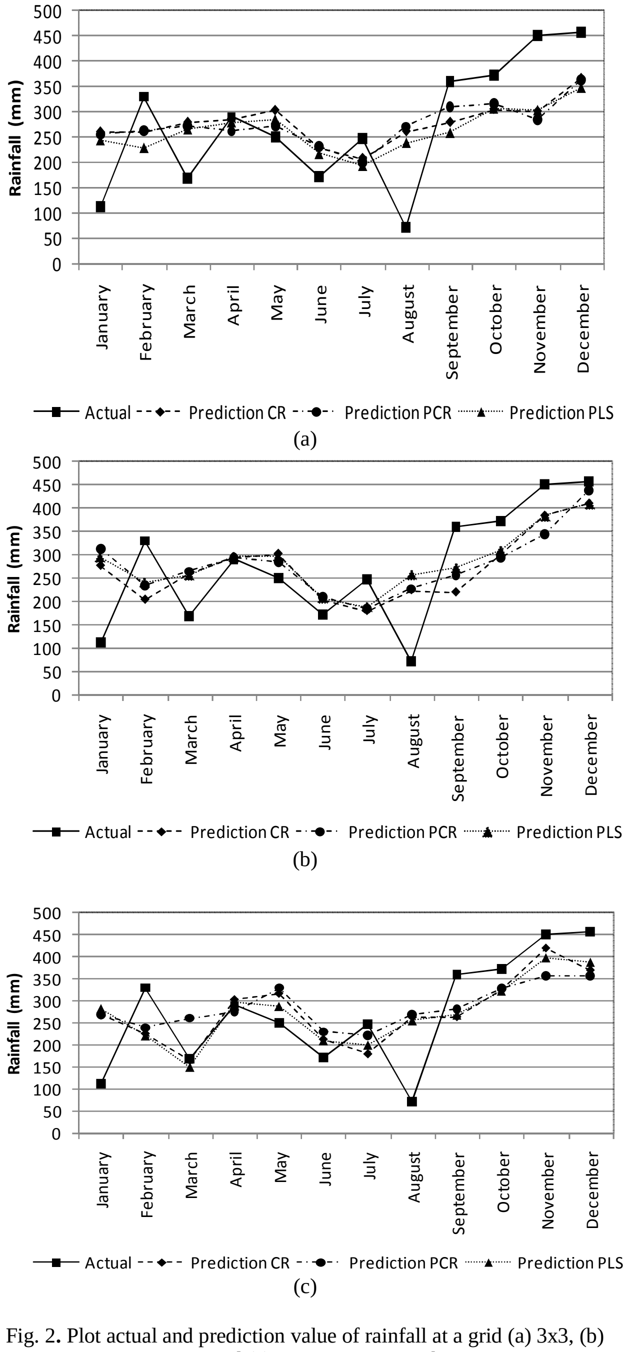


Fig. 2. Plot actual and prediction value of rainfall at a grid (a) 3x3, (b) 8x8, and (c) 12x12 in Pontianak

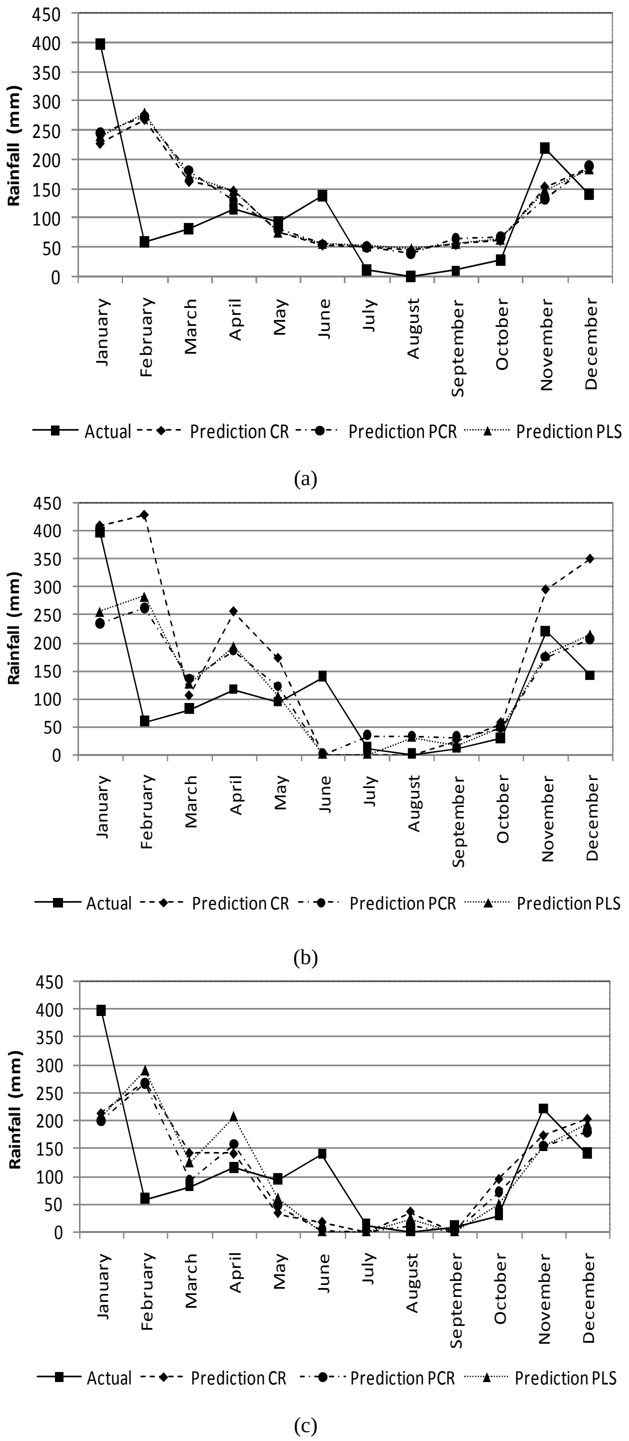


Fig. 3. Plot actual and prediction value of rainfall at a grid (a) 3x3, (b) 8x8, and (c) 12x12 in Losarang

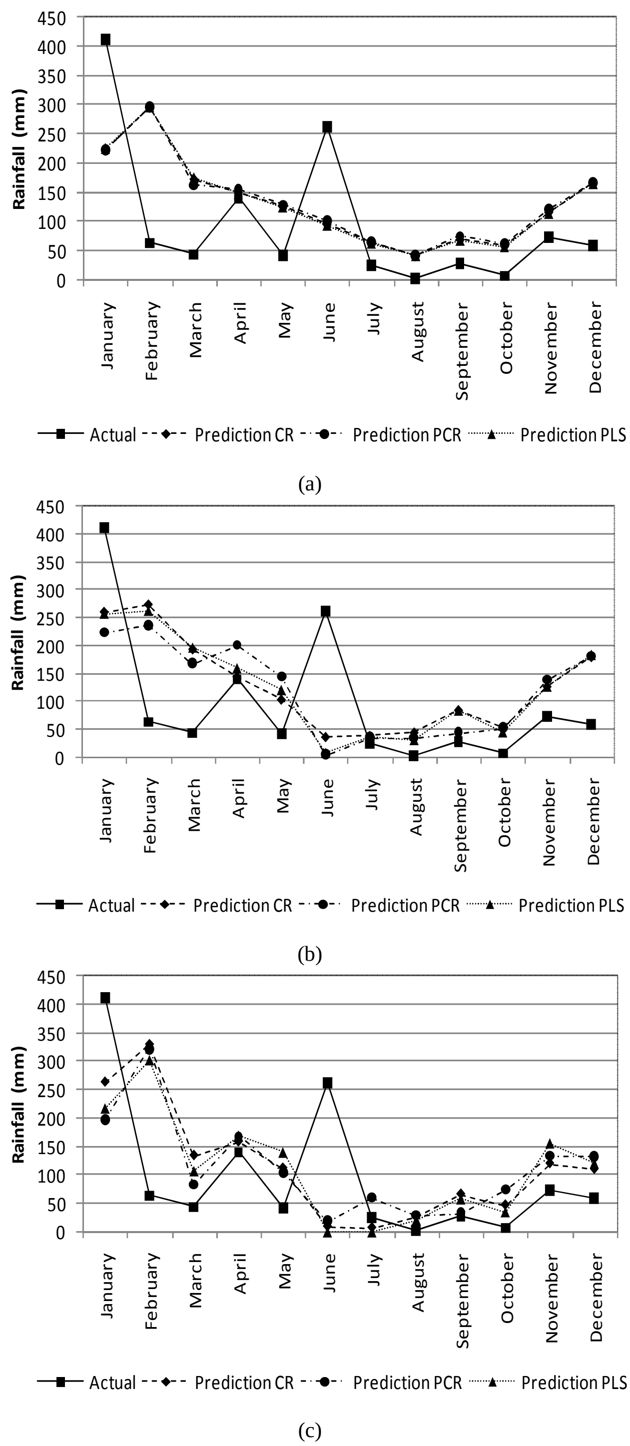
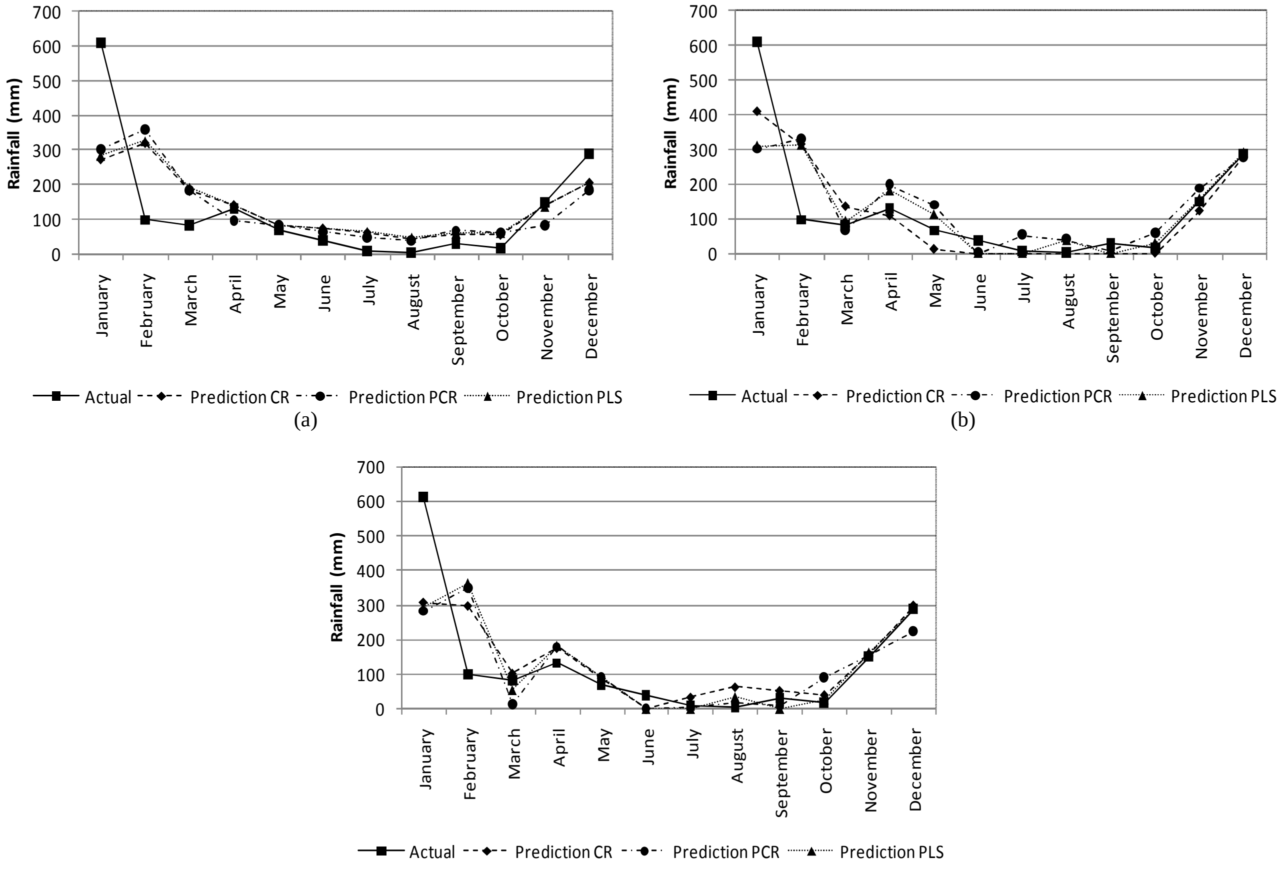


Fig. 4. Plot actual and prediction value of rainfall at a grid (a) 3x3, (b) 8x8, and (c) 12x12 in Yuntinyuat



(a) (b)

(c)

Fig. 5. Plot actual and prediction value of rainfall at a grid (a) 3x3, (b) 8x8, and (c) 12x12 in Indramayu

TABLE 9.
RMSEP AND $R^2_{PREDICT}$ VALUE OF SD *MODELS* BY CR, PCR, AND PLS METHODS

Station	Domain 3x3		Domain 8x8		Domain 12x12	
CR						
	RMSEP	R^2	RMSEP	R^2	RMSEP	R^2
Ambon	246,083	29,60%	247,169	41,00%	248,086	36,80%
Pontianak	101,076	38,20%	97,345	34,50%	92,192	41,40%
Losarang	91,89	30,80%	138,381	41,00%	96,671	27,90%
Indramayu	125,373	44,30%	90,164	70,70%	108,494	58,20%
Yuntinyuat	115,563	15,70%	118,051	14,20%	121,688	13,40%
Mean	136,0	31,72%	138,2	40,28%	133,4	35,54%
Standard deviation	62,9	10,75%	63,8	20,25%	65,1	16,57%
PCR						
Station	Domain 3x3		Domain 8x8		Domain 12x12	
	RMSEP	R^2	RMSEP	R^2	RMSEP	R^2
Ambon	249,448	25,60%	235,012	40,40%	237,806	40,50%
Pontianak	101,264	36,20%	98,527	33,10%	98,931	39,90%
Losarang	93,325	30,00%	93,302	32,10%	96,783	27,60%
Indramayu	128,234	39,70%	118,498	48,90%	126,032	42,10%
Yuntinyuat	115,200	16,20%	123,262	8,20%	126,97	5,80%
Mean	137,50	29,54%	133,70	32,54%	137,30	31,18%
Standard deviation	64,00	9,24%	58,00	15,19%	58,00	15,32%
PLS						
Station	Domain 3x3		Domain 8x8		Domain 12x12	
	RMSEP	R^2	RMSEP	R^2	RMSEP	R^2
Ambon	244,174	30,10%	244,712	39,10%	254,588	33,90%
Pontianak	99,262	41,20%	94,911	39,90%	90,119	44,50%
Losarang	93,188	30,40%	94,271	34,60%	103,714	23,60%
Indramayu	124,930	44,70%	109,974	55,70%	122,043	45,80%
Yuntinyuat	115,440	15,60%	122,721	10,90%	125,784	8,00%
Mean	135,4	32,40%	133,3	36,04%	139,2	31,16%
Standard deviation	62,1	11,40%	63,4	16,16%	66,1	15,76%

Processed by SAS software