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1st International Conference on Mathematics and Its Application

Strengthening Researches on Mathematics for the Challenge of Global Society

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Preface

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PREFACE

The International Conference on Mathematics and its Applications (ICoMathApp) 2020

The International Conference on Mathematics and its Applications (ICoMathApp) 2020 is the first annual conference hosted by the Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Negeri Malang. This conference was held virtually on September 30, 2020 using the platform Zoom. The aim of the conference is to provide a platform to the researchers, experts, and practitioners from academia, governments, NGOs, research institutes, and industries to meet and share cutting-edge progress in the fields of algebra, analysis, applied mathematics, combinatorics, computational sciences, geometry, and statistics. The ICoMathApp 2020 theme “Strengthening Researches on Mathematics for the Challenge of Global Society” is expected to give more contribution from the mathematical aspect as a response to the emerging of Covid-19 pandemic. This conference consists of a plenary and parallel session. The plenary session focuses on comprehensive reviews, concepts and perspectives. Specialized talks on recent developments are presented in the parallel session.

My highest appreciation for the four keynote speakers, Assoc. Prof. Arifah Bahar from Universiti Teknologi Malaysia, Malaysia; Prof. Purwanto, Ph.D from Universitas Negeri Malang, Indonesia; Prof. Hadi Susanto from Khalifa University, Abu Dhabi, & University of Essex, United Kingdom; and Assoc. Prof. Andrea Semaničová-Feňovčíková, Ph.D from Technical University of Kosice, Slovak Republic. My highest gratitude also goes to the invited speakers, Prof. Dr. Basuki Widodo, M.Sc from Institut Teknologi Sepuluh Nopember, Indonesia; Prof. Dr.rer.nat, Indah Emilia Wijayanti, S.Si., M.Si. from Universitas Gadjah Mada, Indonesia; Prof. Dr. Toto Nusantara, M.Si., from Universitas Negeri Malang, Indonesia; Dr. Swasono Rahardjo, M.Si, from Universitas Negeri Malang, Indonesia; and Dr. Desi Rahmadani, S.Si., M.Si. from Universitas Negeri Malang, Indonesia.

We would like to express our gratitude to all authors of contributed papers for participating excellently and eagerly. We hope that all participants in the ICoMathApp 2020 get a lot of insights and knowledge from this conference. We also would like to thank the reviewers for their positive contribution to maintain the quality of the articles presented in this conference. I want to also thank the committee members for their hard work, commitment, and dedication in organizing this conference. Our sincere gratitude also goes to the Journal of Physics: Conference Series IOP Publishing editors and coordinator for their helpful cooperation during the preparation of the proceedings.

Mochammad Hafiizh, Ph.D

Chairman

International Conference on Mathematics and its Application 2020

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Projection pursuit regression in statistical downscaling model using artificial neural network for rainfall prediction

Projection pursuit regression in statistical downscaling model using artificial neural network for rainfall prediction

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Abstract. Rainfall prediction is important for farmers to be used in making policies, especially in areas of agricultural production, include in Indonesia. The availability of information about rainfall requires an accurate forecasting method. The General Circulation Model (GCM) is used in dynamic prediction to obtain rainfall information for one month, but with its low resolution, this model cannot be used to obtain information on a small scale so that a statistical downscaling (SD) model is needed. The Projection Pursuit Regression (PPR) used in this SD includes non-parametric and nonlinear approaches to processing large dimensional data that can describe small dimensions through a projection process. This research is further explained using a neural network-based approach, that is Artificial Neural Network (ANN) in a statistical downscaling model with applications for analysis of events related to rainfall prediction. In this case, the data will be part of the model formation of statistical downscaling. The SD prediction model uses several predictors, where some of these predictors have a physical relationship between the atmosphere and rainfall. The predictor variables are taken from the GCM output, the predictor variables used precipitation.

1. Introduction

Rainfall prediction is important to be used by farmers in making policies, especially for areas that are centers of agricultural production, including Indonesia. The availability of information about the amount of rainfall requires an accurate rainfall forecasting method. One of the most frequently used forecasting methods is time series analysis. To improve the quality of climate information, a general circulation model (GCM) has been developed.

GCM is an important tool in diversity and climate change research [11]. This model describes a number of subsystems of the earth's climate, such as processes in the atmosphere, oceans and land, and is able to stimulate large-scale climates such as GCM can produce well-diversified forms of atmosphere and sea surface temperature. On the other hand, the GCM model has the disadvantage that the low resolution makes this model unable to provide information for detail or small scale. GCM information is still on a global scale, so it is not appropriate to be used as a local scale forecasting model. In this case, the statistical downscaling (SD) model is used to bridge the gap between large-scale GCM and local scales [10].

One of the most important steps in downscaling is to select appropriate predictors [4]. The variable can be used as a predictor if relationship exists between the predictor and response. In this study, the response variable is local rainfall and the predictor variable is precipitation [5]. Precipitation is an important parameter for climate change impact studies [9].

The statistical downscaling approach uses global or regional data. One of the statistical downscaling methods that can overcome non-linear GCM data is projection pursuit (PP). So, in this case the PP method is use to reduce GCM data, which then the reduction results are used for projection pursuit regression (PPR) modeling. The PP method is an alternative method for similar uses to principal component analysis, reducing the multiple variable data dimensions. PP as an estimator of the SD model [9]. Another method used for SD is an artificial neural network (ANN) [8].

Chau in his research entitled The Annual Maximum Flood Peak Discharge Forecasting Using Hermite Projection Pursuit Regression with SSO and LS Method shows promising results from the new hermite-PPR model with Social Spider Optimization and Least Squre algorithms in forecasting the maximum annual peak flood discharge, showing a good level of performance [3]. Agmalaro's research uses statistical downscaling combined with a neural network to predict rainfall in Indramayu regency [1], showing that the overall model produced is good enough to predict rainfall under normal conditions, even though the prediction model has been able to follow the pattern from the observational data but the resulting predictive value has not succeeded in reaching and close to the actual observed value. The results of research from Asyiefa [2], show that the validation of the statistical downscaling model with the PPR method produces the smallest root mean square error prediction (RMSEP) criteria. The pattern between the forecast and observation results shows that the results of rainfall forecasts in the five districts are close to the observational data. So that the statistical downscaling model is a good model for forecasting rainfall. This paper discusses the combined use of the PPR and ANN methods for estimating the SD model.

2. Data and Method

2.1. Data

This study uses two kinds of data, GCM precipitation data and local data. GCM precipitation which is global data used as a predictor variable. Rainfall data in Jember region which is local data used as a response variable. The data used is the daily rainfall data for 2005-2018 from the rain observation station in Jember which is then processed into monthly rainfall obtained from the BMKG Station. This data can be accessed on the BMKG website for the period January 2005 - December 2018. Jember located in latitude ranges from -21.25N to 3.75N and longitude ranges from 101.25E to 126.25E. Meanwhile, GCM data are obtained on the official website of the Royal Netherlands Meteorological Institute http://climexp.knmi.nl. The data obtained for the preprocessing step are divided into two parts, in-sample data and out-sample data. In-sample data are used as learning data to build a prediction model, while out-sample data are used to validate a model whether the model used is valid. Out sample data are used rainfall data from 2005 to 2016, while for in sample data using data for 2017 and 2018.

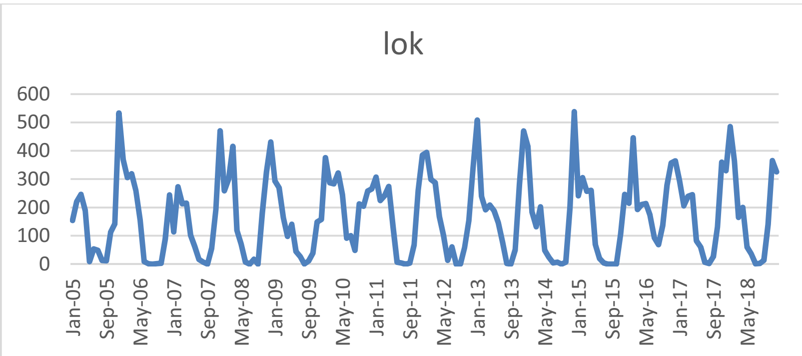

Figure 1. Plot of rainfall fluctuation.

Plot of rainfall data with fluctuations is like on Figure 1, where the highest data or the highest rainfall is in December 2014 with maximum rainfall data reaching more than 500. While for the lowest rainfall occurs in several months of July 2018, August 2011, August 2012, September 2014, August 2015, and September 2015. Twelve years of observed data have consistent fluctuation, each year there is rainfall with low intensity and high intensity. For rain with high intensity occurs from October to April, while the intensity of low rainfall each year has the same fluctuation in May to September.

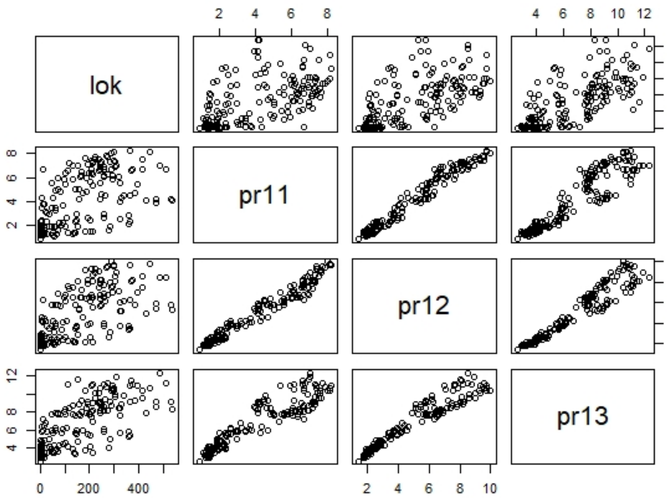

Figure 2. Scatterplot of local rainfall and GCM.

In Figure 2, a scatterplot of local rainfall data and GCM data is presented. After the data is displayed in a scatterplot, the first column and the first row show non-linearity. Therefore, this study uses PPR as a model to reduce non-linear data dimensions. The other rows and columns are the same GCM data from a different domain.

2.2. Method

2.2.1. Projection Pursuit Regression (PPR)

Projection Pursuit Regression (PPR) is one of nonparametric and nonlinear regression methods to process data in large dimensions that can describe information in small dimensions through the projection process [1]. Thus, PPR can solve the problem of local averages, polynomial functions, and recursive partitioning. PPR model begins with maximizing the index projection, determines the functions of a single variable on a basis empirical based on optimum projections, as well add up these functions [7].

Based on Friedman and Stuetzle (1981), the PPR algorithm is as follows.

1. Determine the initial residual value and the value of M (number of functions).

$$r_i \leftarrow y_i, \qquad i = 1,2,\dots,t \tag{1}$$

$$M \leftarrow 0 \tag{2}$$

   where $\sum y_i = 0$. The number of functions is determined based on function optimization m=1,2,3,4,5 and determining the number of functions selected based on the best validation results.

2. Determine $\boldsymbol{\alpha}$ and S_α in the model.
   For linear combination $\boldsymbol{Z} = \boldsymbol{\alpha_m X}$, determined smooth function $\boldsymbol{S\_\alpha(Z)}$ according to the Z values using the projection index $\mathbf{I}(\boldsymbol{\alpha})$. As for the projection index $\mathbf{I}(\boldsymbol{\alpha})$ can be calculated using the following formula.

$$I(\alpha) = 1 - \frac{\sum_{i=1}^{t}\left(r_i - S_{\alpha(\alpha x_i)}\right)^2}{\sum_{i=1}^{t} r_i^2} \tag{3}$$

Determine the coefficient vector α_{M+1} that maximizes $I(a)$ (*projection pursuit*), $\alpha_{M+1} = max_{\alpha}^{-1}(I(\alpha))$ and the smooth function is $S_{\alpha_{M+1}}(Z)$.

3. End of Algorithm
If $\mathbf{I}(\boldsymbol{\alpha})$ smaller than threshold value then it stops. But, if $\mathbf{I}(\boldsymbol{\alpha})$ greater than the threshold value, the residual value and M value are changed as follows.

$$r_i \leftarrow r_i - S_\alpha(Z), \qquad i = 1,2,\dots,t \tag{4}$$

$$M \leftarrow M + 1 \tag{5}$$

And return to the previous step. The threshold value is obtained from the linear combination boundary in the scatterplot between the response variable and the predictor variable. The following is the end of the PPR algorithm:

$$y_i = \sum_{m=1}^{M} S\_\alpha_m(a_m X) \tag{6}$$

$$= \beta_0 + \sum_{m=1}^{M} \beta_m f_m\left(\sum_{k=1}^{n} \alpha_{km} X_{ik}\right) + \varepsilon_i \tag{7}$$

$S\_\alpha_m(a_m X)$ is an unknown function and $\alpha_m = \alpha_{1m}, \alpha_{2m}, \dots, \alpha_{km}$ is a unit vector where m is the basis of the function. $X_i = (X_{i1}, X_{i2}, \dots, X_{ik})$ is the k-th predictor variable and the i-th observation, y_i is a response variable, ε_i is a random vector with $E(\varepsilon_i) = 0$ and $var(\varepsilon_i = \sigma^2)$ [2].

2.2.2. *Artificial Neural Network (ANN)*

Artificial Neural Network Artificial (ANN) is an information processing technique or approach inspired by the workings of the biological nervous system, especially in human brain cells in processing information. The key element of this technique is the structure of the information processing system which is unique and varied for each application. Neural Network consists of a large number of information processing elements (neurons) that are connected and work together to solve a particular problem, which is generally a classification or prediction problem.

Neural networks usually have unique artificial neuron and the model of a multilayer neural network. The signal flow from inputs $x_1, x_2, x_3, \dots x_n$ is considered to be unidirectional, and $w_1, w_2, w_3 \dots w_n$ are associated weights to the corresponding inputs. The acceleration or retardation of the input signals is formed by the weights to account the strength. Hence the total input received is:

$$\boldsymbol{I} = \boldsymbol{w_{1\times 1}} + \boldsymbol{w_{2\times 2}} + \cdots + \boldsymbol{w_{n\times n}} \tag{8}$$

The sum is passed on to non-linear filter called Activation Function Φ which forms the thresholding process. The sum will be compared with threshold value $\boldsymbol{\theta}$, if $\boldsymbol{I} > \boldsymbol{\theta}$ then output is 1, otherwise 0.

$$\boldsymbol{y} = \boldsymbol{\phi}(\boldsymbol{I}) \tag{9}$$

$$\boldsymbol{y} = \sum_{\boldsymbol{i=0}}^{\boldsymbol{n}} \boldsymbol{w_i x_i} - \boldsymbol{\theta} \tag{10}$$

2.2.3. Method Evaluation

In this case, the performance of the PPR model was evaluated using Root Mean Square Error (RMSE). RMSE is performance index to determine the accuracy of the PPR model in predicting the target values [5]. RMSE is a measure of how spread out these residuals or error that has occurred between the test values and the predicted values. A smaller RMSE value indicates a better model, mathematically:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{11}$$

3. Model Development

In this paper, the projection pursuit regression process in statistical downscaling will be explained in this section, as well as the use of artificial neural networks in this study. In the previous section, the data used is GCM data as a response variable and local data as a predictor variables. The size of the domains used in this study are the domains 3x3, 4x4, 5x5, 6x6, 7x7, 8x8, 9x9, 10x10 which had been adjusted to the astronomical location of the Jember district. of each domain size has 9, 16, 25, 36, 49, 64,81, and 100 predictor variables.

There are several steps of Projection Pursuit Regression in statistical downscaling as steps to form a model. The first step is selection number of functions in PPR, based on the description of the PPR method for the function to be tested first where for m = 1,2,3,4,5 which will then be seen from each function of the RMSE value, so that each the domain with the smallest RMSE will be used for the next process.

Table 1. Optimum Number of Functions in PPR.

Domain Size	Banyak fungsi (m)	Nilai RMSE
3×3	$m = 1$	78.70853
	$m = 2$	69.96927
	$m = 3$	55.95357
	$\boldsymbol{m = 4}$	**42.25480**
	$m = 5$	51.50790
4×4	$m = 1$	73.10434
	$m = 2$	69.80424
	$m = 3$	65.32772
	$m = 4$	56.01909
	$\boldsymbol{m = 5}$	**23.95734**
5×5	$m = 1$	63.14675
	$m = 2$	57.55973
	$m = 3$	36.55114
	$m = 4$	32.48607
	$\boldsymbol{m = 5}$	**18.83486**
6×6	$m = 1$	49.90116
	$m = 2$	30.97867
	$m = 3$	21.27827
	$m = 4$	18.98777
	$\boldsymbol{m = 5}$	**15.72641**
7×7	$m = 1$	41.388234

	$m = 2$	22.464495
	$m = 3$	16.153983
	$m = 4$	12.255301
	$\boldsymbol{m = 5}$	**6.099832**
8×8	$m = 1$	45.571702
	$m = 2$	18.718511
	$m = 3$	6.905575
	$m = 4$	3.176746
	$\boldsymbol{m = 5}$	**1.418566**
9×9	$m = 1$	48.992543
	$m = 2$	38.821391
	$m = 3$	2.294679
	$m = 4$	1.366185
	$\boldsymbol{m = 5}$	**0.928577**
10×10	$m = 1$	17.7852544
	$m = 2$	6.9505160
	$m = 3$	2.1768314
	$m = 4$	0.4319677
	$\boldsymbol{m = 5}$	**0.2164227**

For the next step, determine the size of the domain, where each domain is determined by its correlation value. The highest correlation value from the grid indicates the optimum grid size. The optimum grid size is then used to form the PPR model.

Table 2. Domain Size Selection.

	Size grid	Correlation
1	3X3	0.7193563
2	4X4	0.5559191
3	5X5	0.5302808
4	**6X6**	**0.7374709**
5	7X7	0.5115799
6	8X8	0.5431379
7	9X9	0.3952015
8	10X10	0.3822072

From Table 2, the highest correlation value is on the 6x6 grid size with a value of 0.7374709. Therefore, a 6x6 grid is used to form the best model. Then, by obtaining the best model from PPR, the output of the model is the result of monthly rainfall forecasts. Furthermore, it will be compared with the combined results of PPR and ANN. The comparisons shown are the values and plotting from original data, PPR results, and combined PPR and ANN results.

4. Result and Discussion

The best domain is 6x6 grid with 36 predictor variables. The grid is obtained from the optimal correlation value for each grid with the number of functions or m = 5. The data used for the test are the monthly rainfall data for 2017 to 2018. Here are the results of a comparison of real monthly rainfall data, forecasts with the PPR model and forecasts with the PPR model combined with ANN.

Table 3. Comparison of Real Data, PPR model and PPR model combined with ANN.

Periode test	Real Data	PPR	PPR+ANN
Jan-17	294,1818	262,662470	256,2014645
Feb-17	205,7403	415,996499	343,2100269
Mar-17	239,1039	287,368591	273,2710707
Apr-17	245,1429	327,473135	205,5668609
Mei-17	8,24545	20,564512	171,8240208
Jun-17	6,01948	118,471452	40,4452132
Jul-17	6,6364	3,874141	37,5464200
Agu-17	2,5714	163,136201	10,0807324
Sep-17	2,67792	5,202689	52,6427973
Okt-17	131,3766	97,601821	132,8618990
Nov-17	359,4935	198,073421	181,0487558
Des-17	329,4935	451,215129	342,9339555
Jan-18	485,0128	344,834636	357,3399022
Feb-18	363,8718	183,620014	247,4912141
Mar-18	164,9231	245,898806	244,2280915
Apr-18	200,1667	154,458823	138,9676265
Mei-18	60,9359	-4,073062	68,5261666
Jun-18	3,5859	-31,418982	74,3438076
Jul-18	1,4487	108,523183	7,4233488
Agu-18	2,5513	30,176993	-0,1807121
Sep-18	13,7179	46,379388	16,3349645
Okt-18	139,7692	83,947006	49,3318250
Nov-18	365,2308	180,402859	174,6601490
Des-18	325,359	417,240272	355,3202809

From the data in Table 3, it can be seen the comparison between the three values presented. For example, for January 2017 the original data showed potential rainfall with a value of 294.1818, while the PPR model obtained a value of 262.662470, this means that the PPR model is almost the same to real data in January 2017. However, for the PPR model combined with ANN got a value 256.2014645. This shows that the PPR model combined with ANN is better than the PPR model alone. It can be seen from the RMSE results of the two models shown in Table 4.

Table 4. RMSE PPR and RMSE PPR+ANN.

Grid Size	PPR	PPR+ANN
6x6	103.7539	79.58723

Table 4 shows that the RMSE PPR combined with the ANN is smaller than the RMSE PPR model. Therefore, the smaller the RMSE, the best model.

The following is the plot of the results of the comparison of the three data

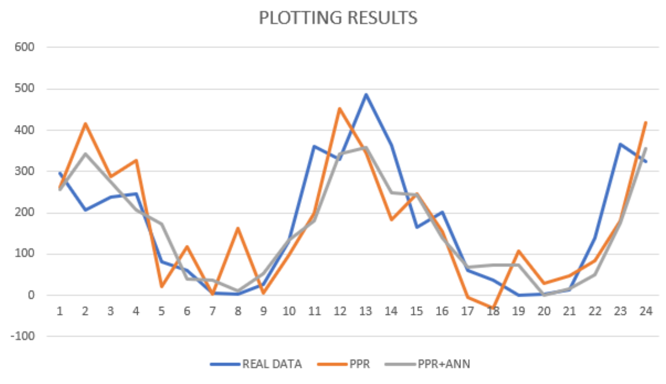

Figure 3. Plotting result of model.

In Figure 3, real data is shown on the chart in blue. The PPR model is shown in orange, while the PPR + ANN is shown in grey.

5. Conclusion

In this study, there are two conclusions that can be explained. Projection Pursuit Regression can be used to reduce dimensions, especially for nonlinear data. The combined performance of PPR with ANN is smoother than PPR without ANN. Model performance comparison based on the RMSE value. Overall, the resulting model is good enough to predict rainfall in the Jember region. Local rainfall data are not clustered, so the RMSE value is quite large. It would be better for further research to predict the rainfall in the Jember area to be clustered into coastal and non-coastal areas to obtain the smallest RMSE value.

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