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A RELATIONSHIP BETWEEN TEMPERATURE AND PRECIPITATION OVER THE CONTIGUOUS BANDUNG CITY, INDONESIA

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Abstract: Temperature and precipitation are important measurements for explaining the climate and can have wide-ranging effects on human life and ecosystems. A warming climate tends to increase precipitation in many areas. Therefore, studying the relationship between temperature and precipitation is crucial for providing information precipitation prediction in many areas. The information on the relationship between precipitation and temperature will be very useful for a lot of fields such as ecological analysis, agriculture, and business. The correlation between monthly total precipitation and monthly mean temperature over the 30-year period from 1970 to 2000 using WorldClim global database data for Bandung city at ~ 1 km^2 resolution was calculated and analyzed. Geographically weighted regression has been used to estimate regression coefficients of mean temperature on precipitation which allow varying over space and time. Regions of both positive and negative precipitation-temperature correlations were found which indicates

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that warm summers tended to be dryer. This particularly true in the northern regions of Bandung.

Keywords: temperature; precipitation; ecosystems; Bandung city.

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1. INTRODUCTION

The environment plays an important role in our lives. Various fields such as agriculture, ecology, health, business, and other fields are strongly influenced by weather changes. However, our knowledge about the weather conditions is very limited [1]. The relationship between weather variables is still interesting to be explored. There is a strong relationship between the amount of precipitation and temperature [2]. The increasing temperature causes an increase in the saturated vapor pressure which influences the amount of precipitation [2]. The modeling precipitation on temperature is an important part of explaining climate change scenarios [2].

The relationship between precipitation and temperature have been explored in several research papers (see [2-8]). In general, they found a negative correlation between precipitation temperature. However, there is a limited study about climate modeling for the small region due to the limited data as a consequence the limited observation weather station meteorology. In small regions, they may have only one observation station. It provides only single data for all sub-region and this information may not be optimal for the other studies. WorldClim global climate database widely used source to retrieve high-resolution GIS climate layers that can be used for any purpose of research. It provides ~1km^2 spatial resolution and has been averaged by month over a 30-year time period from 1970-2000. Here, we intend to complement earlier studies of the relationship between precipitation and temperature the effect of temperature on precipitation over the contiguous small area of Bandung city, Indonesia. We used a dataset from WorldClim global database. GWR statistical modeling was used to estimate the parameter effect of the temperature on precipitation.

The rest of the paper consists of data and methodology in section 2, result and discussion in section 3, and section 4 provides the conclusion.

2. MATERIAL AND METHOD

Material

The data were readily obtained from existing databases. Monthly precipitation and temperature data at the regular grid point of Bandung city for 1 km resolution were obtained from Bandung from WorldClim global climate database. WorldClim has become the most valuable and widely used source to retrieve high-resolution GIS climate layers to be used as a predictor variable for disease modeling. We downloaded the full set of seven monthly climates data included minimum, mean, and maximum temperature, precipitation, solar radiation, wind speed, water vapor pressure, and total precipitation. These products are derived from the monthly weather station. The WorldClim data are at ~1-km^2 spatial resolution and have been averaged by month over a 30-year time period from 1970-2000.

Method

Geographically weighted regression (GWR) was introduced by Brunsdon et al. (1996) [9]. The regression coefficients are allowed to vary over spatial units which are known as a local coefficient. The presentation of the GWR result commonly consists of mapping the local regression coefficient estimate and associated (pseudo) t-value to evidence of non-stationary [10, 11]. The basic form of the GWR model is:

$$y_i = \beta_{i0} + \sum_{k=1}^{K} \beta_{ik} x_{ik} + \varepsilon_i \tag{1}$$

where y_i denote the dependent variable at location i, which is explained by covariates x_{ik} ; $k = 1, \dots, K$ with the varying regression coefficient over space is denoted by β_{ik}. The intercept of the model is labeled as β_{i0} and ε_i is the random error at location i.

Given the Tobler's first law of geography in the fitting model, the GWR model assumes nearer observations have more influence in estimate the local set of regression coefficient than observations farther away [10, 12]. The regression coefficient for each location i is estimated by a weighted least square approach. The matrix expression for this estimation is [12]:

$$\widehat{\boldsymbol{\beta}}_i = (\mathbf{x}'\boldsymbol{W}(u_i, v_i)\mathbf{x})^{-1}\mathbf{x}'\mathbf{y} \tag{2}$$

where $\mathbf{x}$ is the matrix of independent variables with a column of 1s for the intercept, $\mathbf{y}$ denote the dependent variable vector, $\widehat{\boldsymbol{\beta}}_i = (\hat{\beta}_{i0}, \hat{\beta}_{i1}, \ldots, \hat{\beta}_{iK})'$ is the vector of $K+1$ local regression coefficient, and $\boldsymbol{W}(u_i, v_i)$ is an diagonal matrix of dimension n denoting the geographical weighting of each observed data for regression point i at location (u_i, v_i). The weighting $\boldsymbol{W}(u_i, v_i)$ is determined by some kernel function.

Table 1. Six kernel functions; w_{ij} is the j-th element of the diagonal of the matrix of geographical weights $\boldsymbol{W}(u_i, v_i)$, and d_{ij} is the distance between observations i and j, and b is the bandwidth [10].

Model	Spatial Weight Matrix
Global model	$\mathrm{w}_{ij} = 1$
Gaussian	$\mathrm{w}_{ij} = \exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)\right)^2$
Exponential	$\mathrm{w}_{ij} = \exp\left(-\left\lvert\frac{d_{ij}}{b}\right\rvert\right)$
Box-car	$\mathrm{w}_{ij} = \begin{cases} 1 & \text{if } \lvert d_{ij}\rvert < b \\ 0 & \text{otherwise} \end{cases}$
Bi-square	$\mathrm{w}_{ij} = \begin{cases} \left(1 - (d_{ij}/b)^2\right)^2 & \text{if } \lvert d_{ij}\rvert < b \\ 0 & \text{otherwise} \end{cases}$
Tri-cube	$\mathrm{w}_{ij} = \begin{cases} \left(1 - (d_{ij}/b)^3\right)^3 & \text{if } \lvert d_{ij}\rvert < b \\ 0 & \text{otherwise} \end{cases}$

Several methods are commonly used to select the optimal kernel bandwidth for GWR such as a leave one out-cross validation (CV) score [13]. However, CV only account for model prediction accuracy. The Akaike Information Criterion (AIC) has been developed by considering model parsimony, that is, is a trade-off between prediction accuracy and complexity [14]. In practice corrected version of the AIC is used, which unlike basic AIC is a function of sample size.

For GWR this entails function fits using small bandwidths receive a higher penalty (i.e., are more complex) than those using large bandwidth. The AICc formulation is defined as:

$$\mathrm{AIC}_c(b) = 2n\ln(\hat{\sigma}) + n\ln(2\pi) + n\left\{\frac{n + tr(S)}{n - 2 - tr(S)}\right\} \tag{3}$$

where n denote the (local) sample size (according to b); $\hat{\sigma}$ is the estimated standard deviation of the error term; and $tr(S)$ denotes the trace of the hat matrix S. The hat matrix is projection matrix from the observed y to the fitted values $\hat{y}$.

We apply this methodology for each month precipitation and temperature data. The estimating parameters model is used R-software with GWmodel package [10].

3. MAIN RESULTS

The annual cycle monthly precipitation and temperature data from 1970 to 2020 was used.

Table 2. Descriptive statistics of precipitation and temperature

Statistics	Precipitation (mm)	Temperature (^{0}C)
Minimum	52.00	19.30
Maximum	328.00	24.00
Average	189.02	22.63

Table 2 shows the descriptive statistics of precipitation and temperature based on 179 grid-points over the Bandung city. The minimum and maximum precipitation are 52 mm and 328 mm respectively, with its average 189.02 mm. The minimum and maximum temperatures in Bandung are 19.30 ^{0}C and 24 ^{0}C respectively with average around 22.63 ^{0}C.

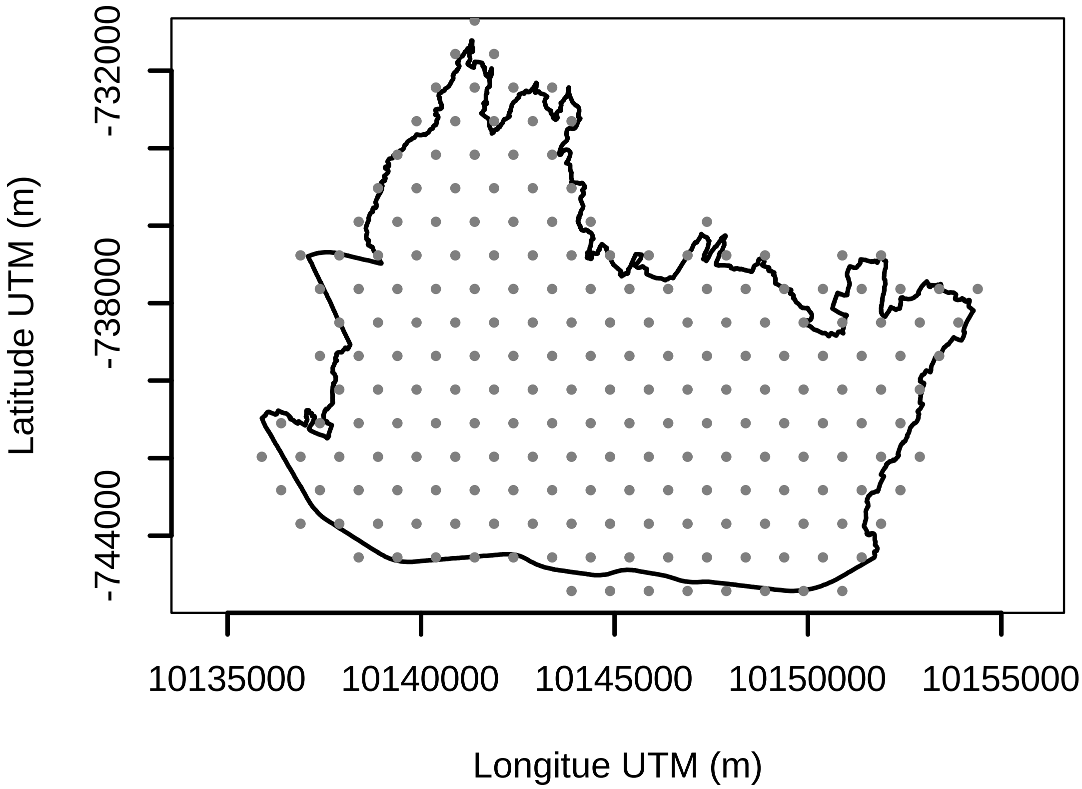
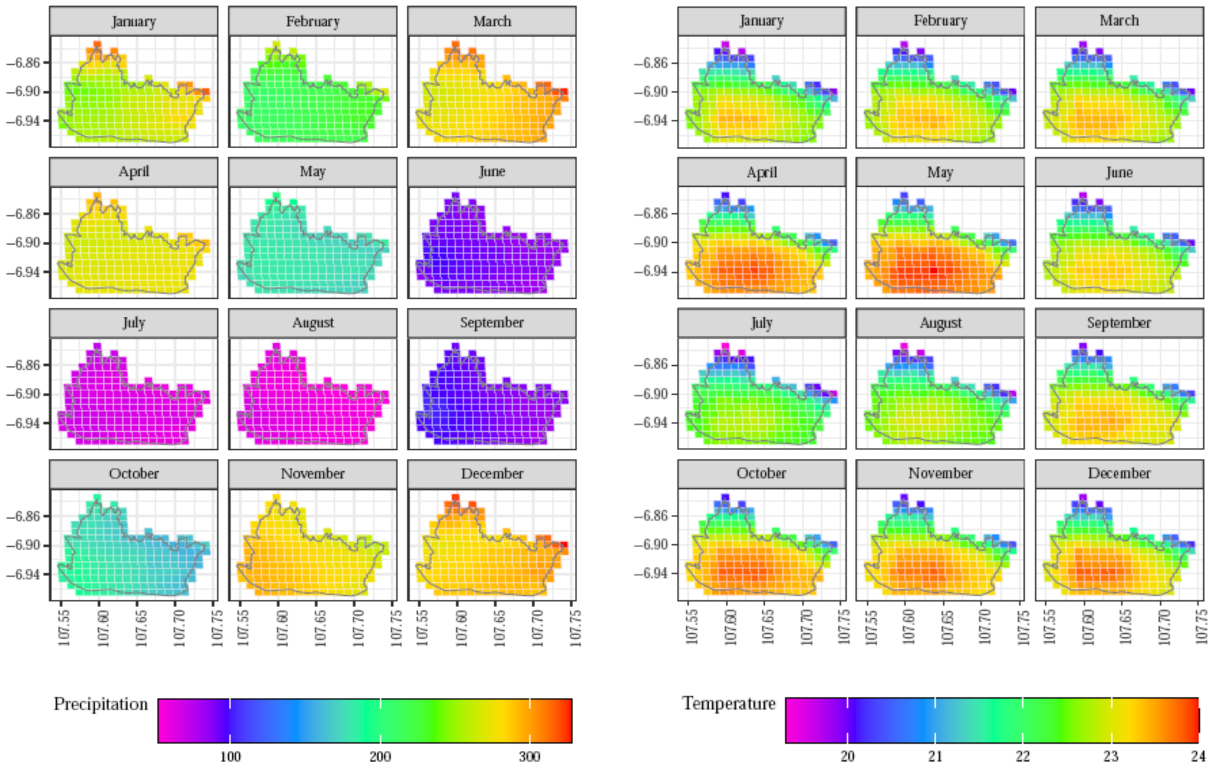


Figure 1. Grid-Points for 1 km^2 resolution

Figure 1 shows the grid-points for 1 km^2 resolution. For each 1 km^2 grid point, a search for the nearby available stations within a threshold distance was conducted. The observation data of the stations found within the threshold distance were interpolated to the grid point using inverse distance weighted (IDW).

Using these grid-points we extracted the monthly precipitation and temperature data from WorldClim global database and the results are presented in Figure 2.



(a) Precipitation (b) Temperature

Figure 2. Spatiotemporal Variation of (a) Precipitation and (b) Temperature

Figure 2 presents the spatiotemporal variation of precipitation and temperature in 1 km^2 resolution grid-points. The precipitation is relatively high between December to May for every year and relatively low between June to September. Temperature is relatively high from September to May and the rest of the months the temperature relatively low. The precipitation and temperature look different for several regions in Bandung especially in Northern and southern parts Bandung. The northern regions of Bandung have high precipitation with low temperatures. While for southern regions of Bandung, the precipitation is relatively low at high temperatures.

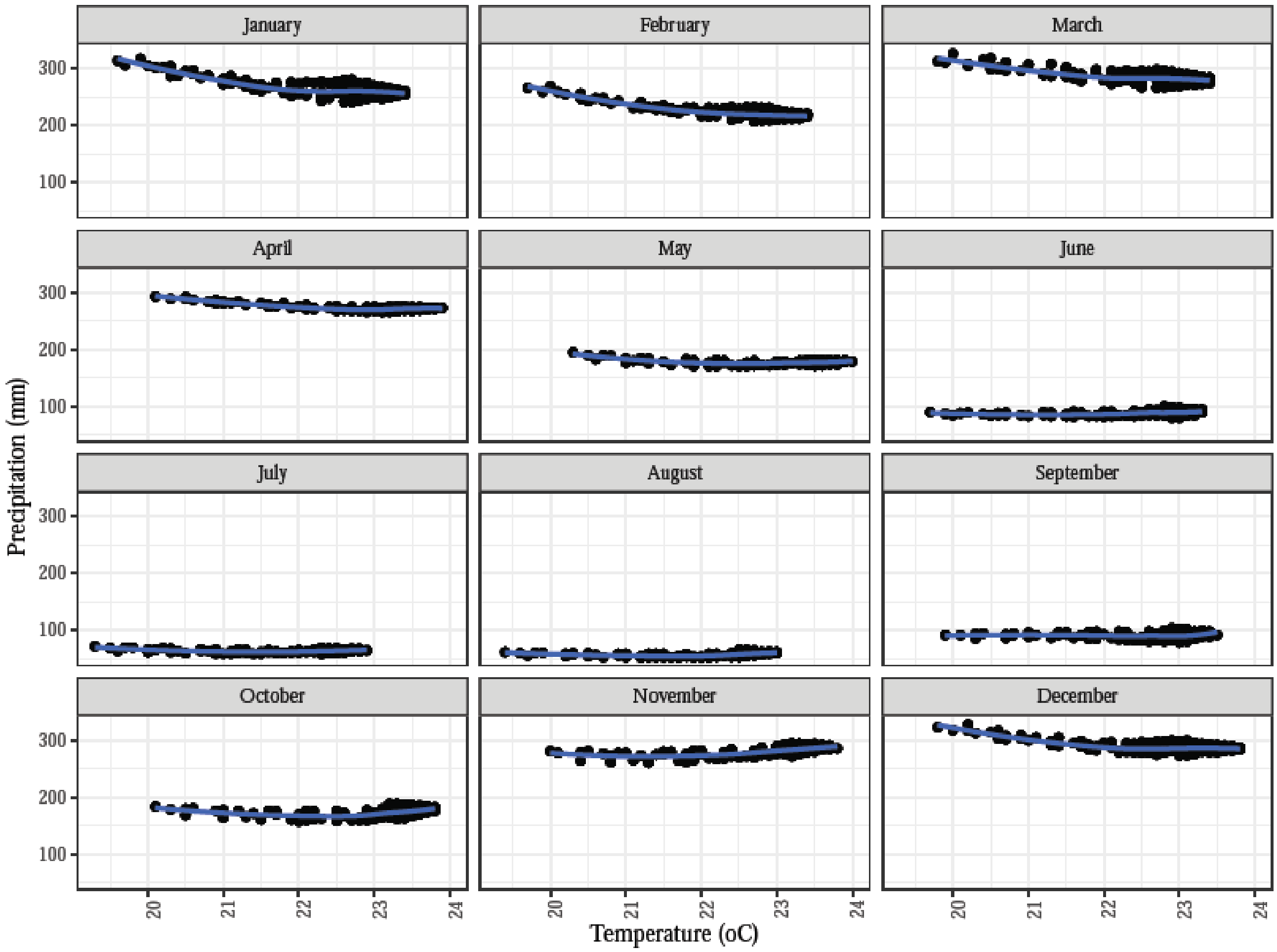


Figure 3. Relationship precipitation versus temperature

Figure 3 shows the relationships between precipitation and temperature by month. We can see there are different relationships for several months. On period January to May and December, the relationship seems to be negative, however, for other months it seems to be positive. It is important to explore the relationship between precipitation and temperature that allow the regression coefficient to vary over the contiguous and time. Here we present the GWR for monthly data of Bandung city. Given the minimum AICc criterion, we used a bi-square spatial weight matrix.

Table 3. Global and local regression parameters estimate

Month	Estimate	Global Estimate			Local Estimate				
		Mean	Std. Err	t	Min.	1st Q	Median	3st Q	Max.
Jan	Intercept	526.55	8.59	61.28	–978.70	154.64	318.40	570.46	858.20
	Temperature	–11.72	0.38	–30.55	–27.58	–14.05	–2.61	4.93	54.00
Feb	Intercept	470.33	5.93	79.36	–317.69	111.61	283.56	464.03	743.77
	Temperature	–11.02	0.26	–41.84	–24.36	–10.73	–2.69	4.58	23.13
Marc	Intercept	469.80	7.53	62.39	–101.11	246.20	469.35	605.29	840.71
	Temperature	–8.21	0.33	–24.60	–24.00	–13.90	–8.26	1.52	16.33
Apr	Intercept	360.37	3.08	117.12	–37.41	195.68	278.11	393.60	518.61
	Temperature	–3.80	0.13	–28.41	–11.30	–5.29	–0.26	3.18	13.18
May	Intercept	201.30	3.36	59.94	–704.00	–23.88	110.45	208.28	434.84
	Temperature	–1.02	0.15	–7.01	–11.86	–1.31	3.03	8.44	36.00
Jun	Intercept	51.93	3.79	13.69	–894.54	–115.57	20.11	79.18	666.50
	Temperature	1.62	0.17	9.65	–25.00	0.26	3.01	8.82	42.95
Jul	Intercept	66.28	2.43	27.26	–351.10	–87.10	14.80	106.13	565.46
	Temperature	–0.10	0.11	–0.92†	–22.31	–1.84	2.13	6.74	18.59
Aug	Intercept	31.37	2.81	11.15	–779.62	–104.02	6.91	81.85	227.39
	Temperature	1.20	0.13	9.51	–7.20	–1.09	2.23	7.18	37.50
Sep	Intercept	86.27	5.98	14.42	–404.00	–142.97	61.24	114.41	506.10
	Temperature	0.22	0.26	0.85†	–17.63	–1.12	1.55	10.00	21.26
Oct	Intercept	123.30	7.25	17.02	–843.58	–116.77	59.43	232.06	819.69
	Temperature	2.19	0.32	6.95	–26.92	–2.56	4.73	12.35	43.16
Nov	Intercept	154.93	5.72	27.07	–751.50	16.89	127.52	242.94	613.18
	Temperature	5.55	0.25	22.16	–13.71	1.49	6.67	11.39	45.00
Dec	Intercept	442.89	5.98	74.06	–461.90	161.25	310.60	508.95	736.78
	Temperature	–6.77	0.26	–25.78	–20.94	–9.60	–1.19	5.40	32.00

†) the effect is not significant

Table 3 shows the global and local regression coefficients of monthly temperature on precipitation in Bandung city, Indonesia. Based on global coefficients, we can see that several months have negative coefficients with indicates there is a negative relationship between temperature and precipitation. The negative coefficient can be found in January until May and December. In these months the precipitation relatively high. However, global effects could be misleading. The effect of the temperature could be positive or negative for different regions in Bandung. Using the local regression model, we found for several regions in Bandung, they have a negative local regression coefficient and for the other were positive. It is important results that inform every part of Bandung may have different characteristics such as elevation, business area, or forestry.

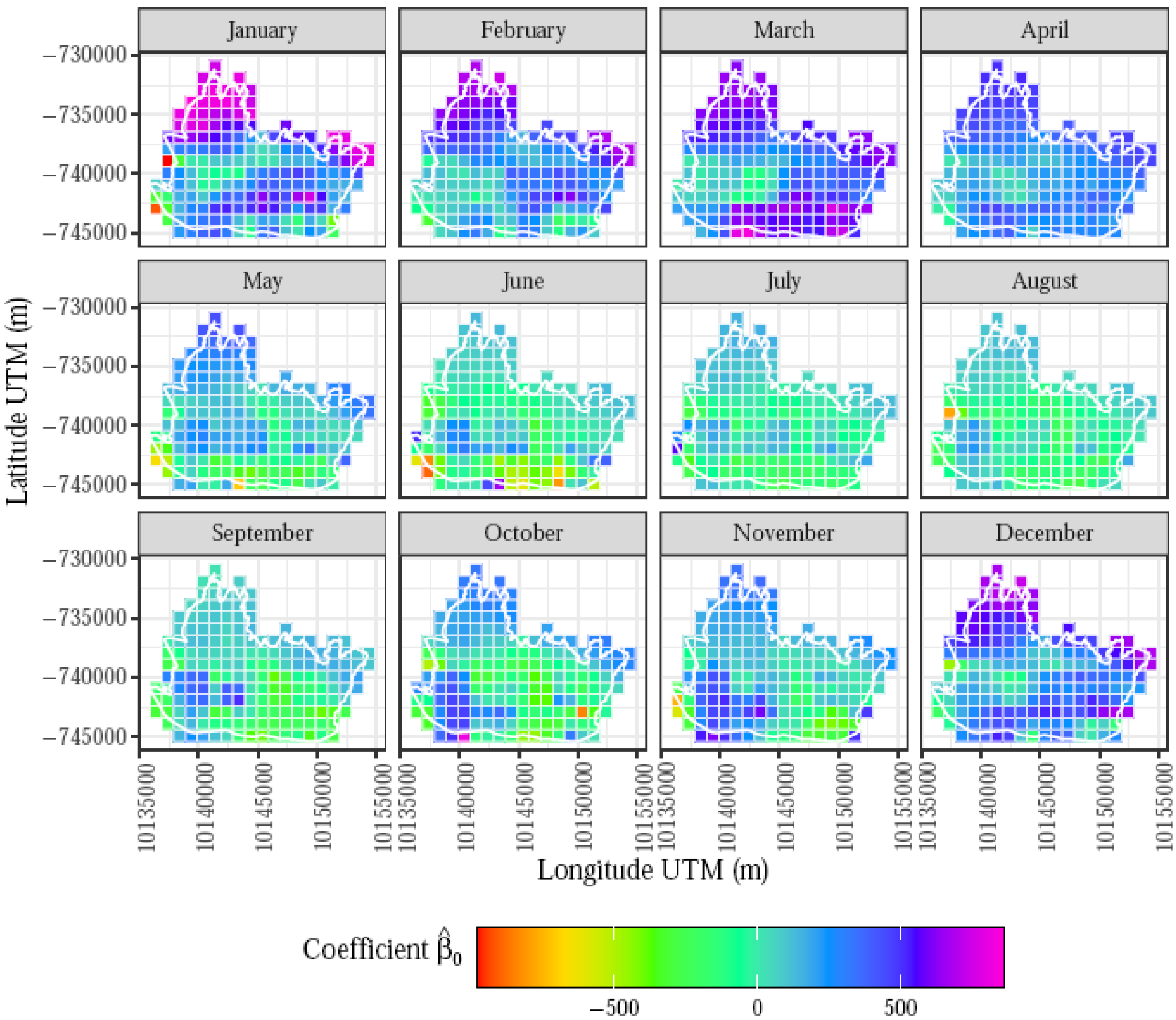


Figure 4. Varying intercept $(\hat{\beta}_0)$

Figure 4 presents the intercept, that is, the average of precipitation is relatively high from December to April especially for northern regions of Bandung.

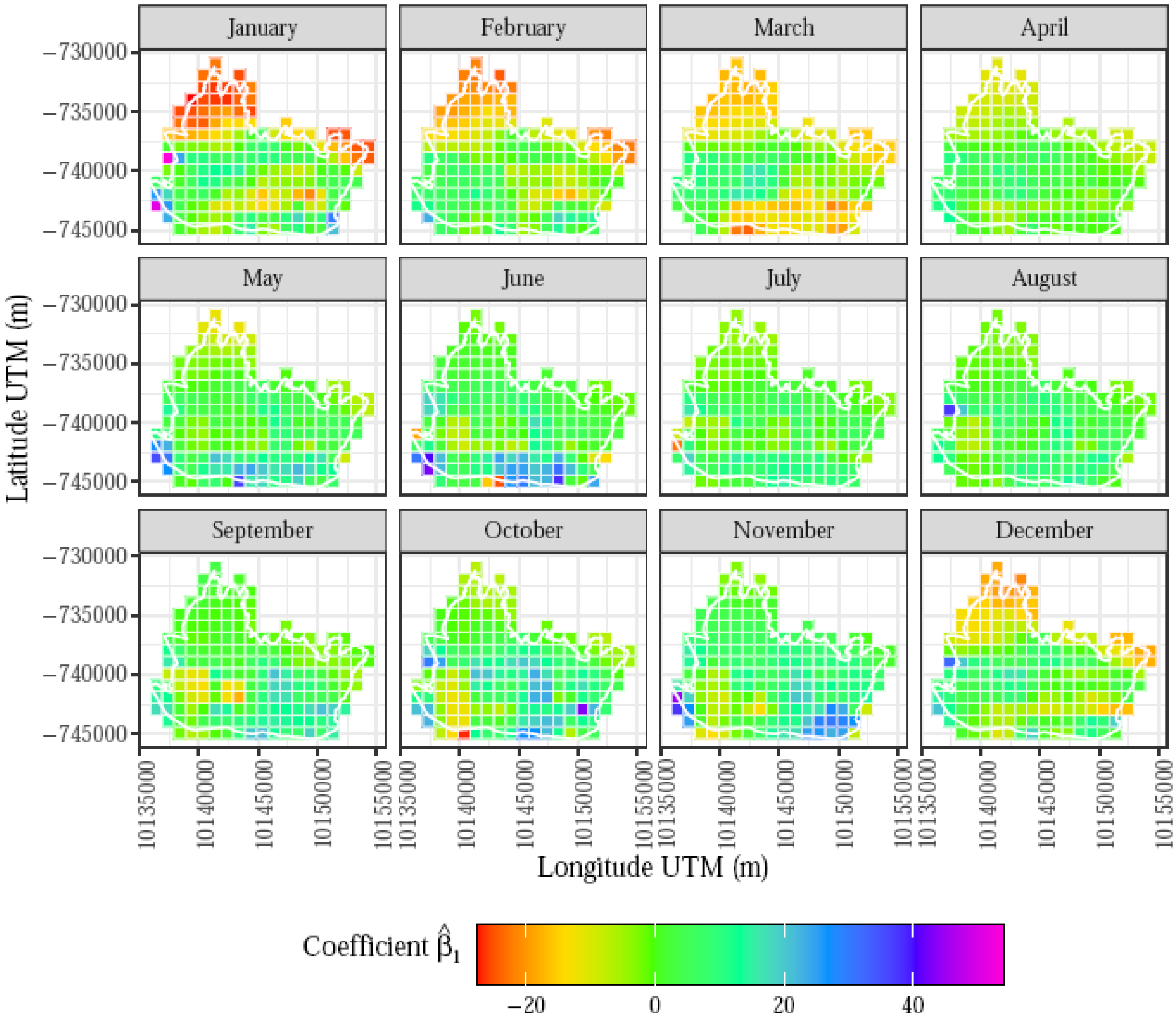


Figure 5. Varying intercept $(\hat{\beta}_1)$

Figure 5 shows the varying slopes over grid-points which explain the relationship between the temperature and precipitation over the contiguous Bandung city, Indonesia. Some regions have positive coefficients and the other have negative coefficients. In general, the high-temperatures are followed by the high precipitations.

4. Discussion and Conclusion

Precipitation and temperature are two common weather variables that have a major contribution to our daily life. For small areas such as the city level, the number of observation weather stations is very limited. Bandung city with the area around 167.7 km² only has one observation weather station. Therefore only a single value of each weather variable can be reported for 30 districts in Bandung. In fact, the weathers condition may vary for each location in Bandung. WorldClim global climate website provides a good prediction for climate variables around the world including Indonesia. Using, database from WorldClim we can obtain the prediction weather variables until ~1 km^2 resolution. We can utilize these weather variables from WorldClim data database to make a useful model for evaluating the relationship between weather variables and making a prediction model. In this study, we focus on providing high-resolution maps of precipitation and temperature in Bandung and evaluating its relationship which allows varying over space and time. This information is required for several purposes such as east controlling disease transmission, flood control, and also agriculture. We applied a Geographically Weighted Regression model to evaluate the relationship between precipitation and temperature. We found the precipitation and temperature vary over space and time and also its relationship. The high relationship between precipitation and temperature was found in the period from January to March for every year especially in the northern regions of Bandung. The effect of temperature on precipitation was negative. It indicates, at northern regions of Bandung, the increasing temperature is followed by decreasing precipitation. However, the temperature in northern Bandung is relatively cold which indicates the precipitation is relatively high. This information can be utilized to explain several phenomena such as the ecological reasons for disease transmission in the northern regions of Bandung.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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