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The Impact of Vegetation on the Local Variations of Rainfall

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ABSTRACT

Rainfall is one of the microclimatic variables that vary with space. The changes in vegetation characteristics may influence the microclimate elements. To demonstrate rainfall variation due to vegetation, the relationship between rainfall and vegetation should be spatially investigated over a local scale. This paper aims to explore the impact of vegetation on local variations of rainfall based on Geographically Weighted Regression (GWR) approach. The global and local relationship between rainfall and the extracted Normalized Difference Vegetation Index (NDVI) of Landsat 7 ETM+ are quantitatively estimated in 2000 and 2011 within the northern and east coast regions of the Peninsular Malaysia. Based on 277 rainfall stations, the Moran's Index (Moran's I) spatial autocorrelation and Ordinary Least Square (OLS) - GWR methods were applied to analyse the rainfall spatial patterns and to determine rainfall spatial variation, respectively. It was found that, the rainfall spatial patterns exhibit small clustering patterns which leads to non-stationarity. This indicator supports the use of local regression approach in exploring the variation of rainfall due to vegetation. The R-Squared (R^2) from GWR (0.51 and 0.75) significantly improved the R^2 from OLS (0.01 and 0.04) for both years. The approach of GWR in the relationship between rainfall and vegetation provides findings on rainfall spatial variation on a local scale.

Keywords: GWR, Moran's I spatial autocorrelation, NDVI, OLS, rainfall spatial variation

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INTRODUCTION

In hydrological cycle, precipitation is the most important component that provides water to the surface of the earth. The variation of precipitation over land area is always related to the changes in global climate. Climate change induces the amount, intensity, frequency and types of precipitation (Ackerman & Knox, 2011; Arnel, 2002; Ward & Trimble, 2004). At the micro-scale level, spatial variations of the earth's surface characteristics also has a significant impact on the spatial pattern and variations in rainfall.

Vegetation degradation is the result of human activities which led to Land Use Land Cover (LULC) and climate changes. In most cases, the amount of precipitation affects the vegetation patterns of the particular area. However, the effects of latent heat occurring due to deforestation also changes the precipitation pattern and distribution as reported by Avissar and Werth (2005). Thus, the spatial distribution of rainfall can also be influenced by vegetation loss due to land degradation e.g., deforestation and urbanization. As a result of deforestation, the biomass reduction and deterioration in forest area is the main factor for increasing heat. As mentioned by Morie (2007), vegetation degradation increases the frequency of flood since the spatial and temporal rainfall patterns are influenced by urbanization. It can also be seen as the impact of urbanization on the local precipitation for urban areas of developed countries as shown by Shepherd and Mote (2009), and Kishtawal, Niyogi, Tewari, Pielke and Shepherd (2010). Another study carried out by Nicholson (2000) also supported the impact of vegetation degradation on rainfall variation at a larger scale; since land surface features such as vegetation cover are an element that can be correlated with fluctuations in rainfall intensity. Thus, the impact of the rainfall local variability due to vegetation degradation should be investigated.

The earth observation monitoring system has been implemented to support the evidence of critical issues such as vegetation degradation. Remote sensing imagery is the most practical and applicable approach to describe the behaviour of vegetation covers over a wider range of spatial scale. Spectral vegetation indices are one useful approach used to assess the vegetation characteristics such as biomass, plant stress, plant health and crop productions as revealed by Jackson and Huete (1991). The most common vegetation index utilized to measure the amount of vegetation is Normalized Difference Vegetation Index (NDVI), which has been implemented by Tucker (1979) to monitor vegetation healthiness. Lillesand and Kiefer (2004) also mentioned that the health of green vegetation can be characterized based on the interaction of the energy in the spectral visible red (0.58-0.68 micrometres) and near-infrared (0.75-1.1 micrometres). Thus, NDVI algorithm of satellite images can be obtained from the ratio of the visible and near infrared band/channel (see equation 1).

$$NDVI = (NIR - RED) / (NIR + RED) \qquad (1)$$

Usually, global spatial statistics are used to determine the spatial relationship between variables. Occurrences of variation, which can be determined by the non-stationary variables such as rainfall, are not completely interpreted and represented. The global spatial statistics in OLS only provides a general indicator to define the relationship between variables. Foody (2003), and Propastin, Kappas and Erasmi, (2008) found the OLS approach is only suitable to quantify the relationship at global and regional scales. However, significant hidden phenomena over location-based occurrences in the non-stationary variables are seldom proven (such as the relationship between rainfall and vegetation) since local variation is hardly measurable.

To show existence of spatial variation, local statistical approach such as the Geographically Weighted Regression (GWR) is more applicable. GWR provides an appropriate basis to investigate the relationship between variables (Fotheringham, Brunsdon, & Charlton, 2002). A study carried out by Foody (2003) revealed that OLS regression model demonstrates poor descriptions in the relationship between NDVI of NOAA AVHRR imagery and rainfall depth when the results are found with minimum R^2 of 0.67 as compared to GWR regression model with the increased R^2 to 0.97. Yuan and Roy (2007) also revealed the improvement of GWR results compared to OLS in the relationship between NDVI of NOAA AVHRR imagery and rainfall with the increase R^2 value from 0.24 to 0.67. Research carried out by Usman, Yelwa, Gulumbe, Danbaba, and Nir (2013) proved that GWR a reliable approach in the prediction of the climatic variable such as rainfall and NDVI at local circumstances. Studies such as Zhao, Gao and Wang (2014), and Georganos (2016) are based on the influence of rainfall in the variations of NDVI where rainfall is selected as the exploratory variable.

Local varying relationship between microclimate elements and rainfall as founded in the vegetation-rainfall relationship can be used to define the impact of vegetation towards rainfall spatial variation. In this study, the impact of vegetation to rainfall spatial variation is analysed. The objectives are: (I) to examine the rainfall non-stationarity based on the rainfall spatial patterns; and (II) to determine the local variation in the relationship between rainfall and vegetation.

MATERIALS AND METHOD

Overall Methodology

The methodology of this study is illustrated in Figure 1, and begins with data acquisition, data processing, spatial patterns analysis, spatial variation analysis and maps to show the variation of rainfall. The main data are rainfall depths and Landsat 7 satellite images. As the first objective is to examine the spatial non-stationarity of rainfall, the spatial autocorrelation test has been carried out using Moran's I methods. This is followed by two (2) regression methods i.e. OLS and GWR to determine the rainfall spatial variation based on the relationship between rainfall and vegetation. The final results of this study are the parameter estimated maps represented by the distribution of rainfall spatial variation and their significant identifiable locations.

Study Areas and Datasets

The study area covers states in the (i) northern and (ii) east coast regions of Peninsular Malaysia, i.e. Perlis, Kedah, Pulau Pinang, Perak, Kelantan and Terengganu; an area of 60450 sq. km. The rainfall depths are obtained from 174 and 103 rainfall stations which contributed to 277 data. Figure 2 shows the location of the study areas and rainfall stations.

The main data used are rainfall depths acquired from the Malaysian Department of Irrigation and Drainage (DID). The rainfall descriptive statistics of the study area for 1996-2011 are shown in Table 1 and Figure 3, respectively. Most of the annual rainfall depths are above of the Malaysian Annual Average except in 1998, 2002, 2005 and 2006. Meanwhile, there are seven sets of annual rainfall in 1999, 2000, 2003, 2007, 2008, 2009 and 2011are above of the long-term rainfall average. The highest and lowest annual rainfall depths are identified in 2009 (3149 mm) and 1998 (2413 mm), respectively.

Satellite images of Landsat 7 ETM+ are used to extract NDVI value of the sampling stations. All satellite images are downloaded from United States Geological Survey (USGS) website. Based on the selected study areas, seven scenes of satellite images have been acquired. The NDVI datasets have been produced in Erdas Imagine 2014 software. Figure 4 shows the selected scenes of Landsat 7 ETM+ used in study area.

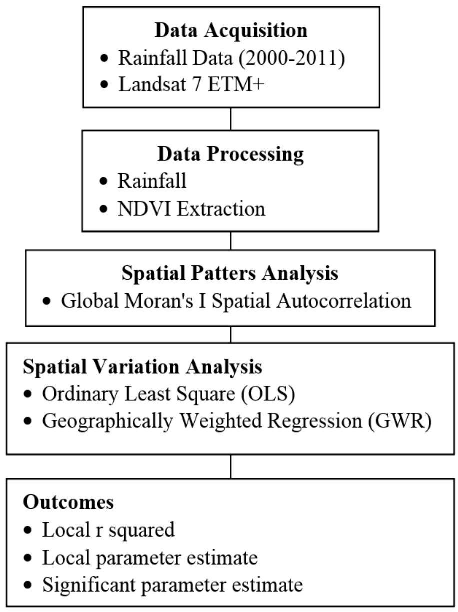


Figure 1. Overall methodology

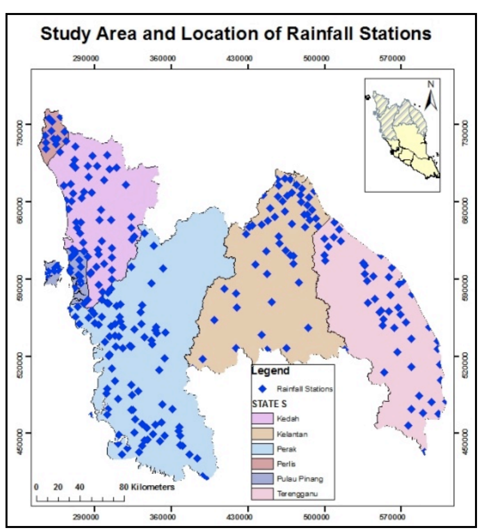


Figure 2. Map of study areas

Table 1
Summary of rainfall descriptive statistics 2000-2011

Year	Annual Average (mm)	Maximum (mm)	Minimum (mm)	Standard Deviation
2000	2591	5486	316	692
2001	2530	5992	702	871
2002	2413	5853	900	621
2003	2995	5726	926	753
2004	2818	5288	185	880
2005	2626	5222	984	894
2006	2347	4043	222	661
2007	2814	8712	1151	926
2008	2543	6464	172	760
2009	2435	4396	894	833
2010	2495	4719	831	636
2011	2734	5726	1083	701

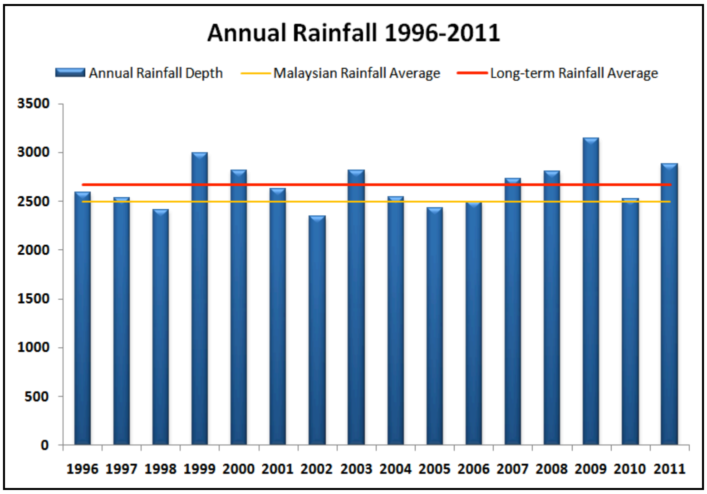


Figure 3. Average of rainfalls for 1996-2011

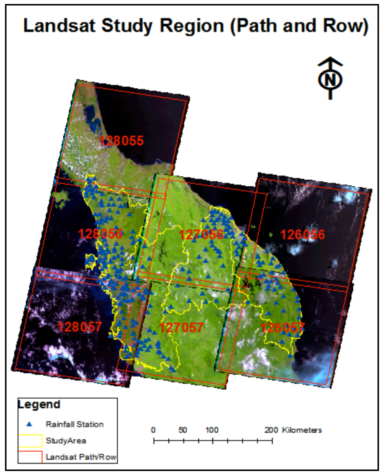


Figure 4. Landsat scenes of study area

Spatial Autocorrelation Tests

The homogenous or heterogeneity behaviour of the investigated variables can be defined via spatial autocorrelation test. In other words, spatial dependency between variable can be identified including the rainfall spatial dependency of that particular area. It can be related to the Tobler's Law of geography in Tobler (1970) where it was stated as, *'everything is related to everything else, but near things are more related than distant things'*. According to Lloyd, 2011, spatial autocorrelation can be measured globally and locally with the concept of geographical versions of univariate statistics approaches. Spatial autocorrelation test based on Moran's statistics was introduced by Moran (1950) to study the vegetation impact on rainfall spatial variation. In this study, the test was used to examine the significant spatial patterns of rainfall and help in the selection of the appropriate regression method for rainfall-NDVI relationship. The equation of Global Moran's spatial autocorrelation coefficient, I is shown by Equation 2:

$$I = \frac{\sum_{i=1}^{J} n(R_i - \bar{R})(R_j - \bar{R})}{\sum_{i=1}^{n} J(R_i - \bar{R})^2} \tag{2}$$

Where n is the total number of areas, J is the total number of joints, R_i and R_j are the values of rainfall density for two contiguous areas, and $\bar{R}$ is the overall mean of rainfall. Results of Global Moran's I vary from -1 to +1. The interpretation of Moran's I results is based on the computed P-Value and Z-Score.

Global and Local Regression Approach

The relationship between variables can be determined using regression analysis. The common technique used in regression analysis is simple linear regression such as Ordinary Least Square (OLS) method. This method can be used to demonstrate the relationship among variables at global scale. In this study, the relationship between rainfall (R) and its influencing factors such as vegetation (y) can be estimated using Equation 3:

$$y = \beta_0 + \beta_1 R_1 + \cdots . + \beta_n R_n + \varepsilon \quad (3)$$

Where β_0 - β_n are the estimated parameter that indicates the relationship between the y and R, and R_1 - R_n values of rainfall density and   is an error term.

Based on the global approach of OLS, the relationship between variables can locally be explored depending on the behaviour of the variables. A local regression technique called Geographically Weighted Regression (GWR) such as found in Brunsdon, Fotheringham and (1998), and Fotheringham, Brunsdon and Charlton (2002) has been widely used to locally explore the spatial non-stationarity of variables. The local variation in the relationship between rainfall (R) and other variables such as vegetation (y) can be investigated at individual location (μ,v) using GWR model such as shown in Equation 4:

$$y = \beta_0(\mu, v) + \beta_1(\mu, v)R_1 + \cdots . + \beta_n(\mu, v)R_n + \varepsilon \quad (4)$$

In this study, NDVI which represents the vegetation areas is assigned as the independent variable and rainfall density as the dependent variable. Both regression method i.e. OLS and GWR were used to demonstrate the relationship between rainfall and NDVI at global and local scales. All regression processes were carried out using GWR 4.0 application software developed by Nakaya, Fotheringham, Charlton and Brundsdon, (2009).

RESULTS AND DISCUSSION

Rainfall Spatial Patterns of Study Area

Rainfall spatial patterns have been demonstrated based on Moran's I spatial autocorrelation available in ArcGIS 10.1 software. The graph of rainfall spatial autocorrelation of 2000 and 2011 is shown in Table 2 and found to be clustered in the significant level of 0 (P-Value) with the critical value (Z-Score) of >2.58. The Moran's Index has low values of 0.305 and 0.534, and Z values at 13.75 and 23.71 respectively. Indicating spatial patterns of rainfall in 2000 and 2011 have a small clustering pattern. This indicator supports the nature of rainfall non-stationarity such as mentioned by Brunsdon et al. (1998) that rainfall varies with location and are not homogeneous throughout the dataset. Thus, the exploration of rainfall-NDVI relationship at the local level can be performed based on the local regression technique, i.e. GWR.

Relationship between Rainfall and Vegetation

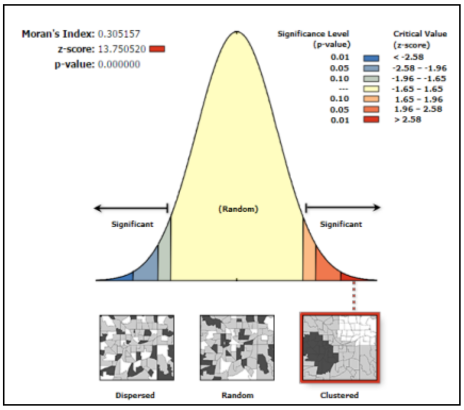
Based on two datasets of the study area, the global and local regression between rainfall and NDVI derived from Landsat 7 ETM+ are carried out. The results for both datasets (see Table 3) shows improvement of R^2 from OLS to GWR with the value of R^2 from OLS (0.01 and 0.51) to GWR (0.04 and 0.75) in 2000 and 2011, respectively. The indicator from Akaike Information Criterion (AIC) is used to assess the quality of the relationship established from

OLS and GWR. The results of AIC were found reliable where the AIC values from GWR are found to be lower than AIC of OLS. The map of local R^2 from GWR in 2000 and 2011 are shown in Figures 5(a) and 6(a), respectively.

The results of local parameter estimates of GWR are tabulated in Table 3. To visualize the relationship between rainfall-NDVI at a local scale, the results of GWR should be spatially distributed on the map based on two conditions as demonstrated by Matthews and Yang (2012). i.e., estimation of local coefficient (II) local t-value to identify the significance level.

Table 2
Summary of Global Moran's I annual rainfall between 2000 and 2011

2000	2011
Moran's Index = 0.31	Moran's Index = 0.53
z-score = 13.75	z-score = 23.71
p-value = 0	p-value = 0



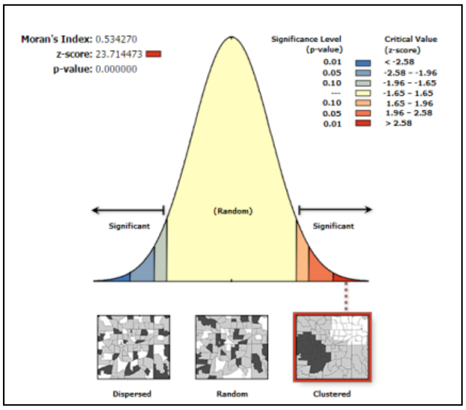


Table 3
R^2 Parameter estimate (Global and Local)

Regression Methods	R^2		AIC	
	2000	2011	2000	2011
Global (OLS)	0.01	0.04	4544.05	4261.91
Local (GWR)	0.51	0.75	4459.72	3954.63
Local Parameter (Gwr	Variables			
	Intercept		NDVI	
	2000	2011	2000	2011
Minimum	1784.24	187520	-2046.69	-1703.16
Lower Quartiles	2421.41	2336.19	-396.82	45.72
Median	2919.39	2779.63	167.45	207.15
Upper Quartiles	3170.79	3376.29	632.45	644.45
Maximum	3996.13	4620.92	3128.16	1702.03

The GWR maps of Rainfall-NDVI R^2 for 2000 and 2011 are shown in Figures 5(a) and 5(b), respectively. The NDVI estimated coefficient in the relationship between rainfall-NDVI are shown in Figures 5(c) and (d)). With 95% level of confidence, the significant locations indicate l-NDVI correlation in 2000 and 2011 as shown in Figures 6(a) and (b). In 2000, a total of 228 locations were found at 95% level of confidence. However, the locations with 95% confidence level in 2011 increased to 248 stations. It was found that most of the significant locations in 2000 are within the northern region with increases in the east coast region in 2011. Based on the associated local t values for NDVI of 2000 and 2011, the identified significant locations for both parameters are mapped as in Figure 7.

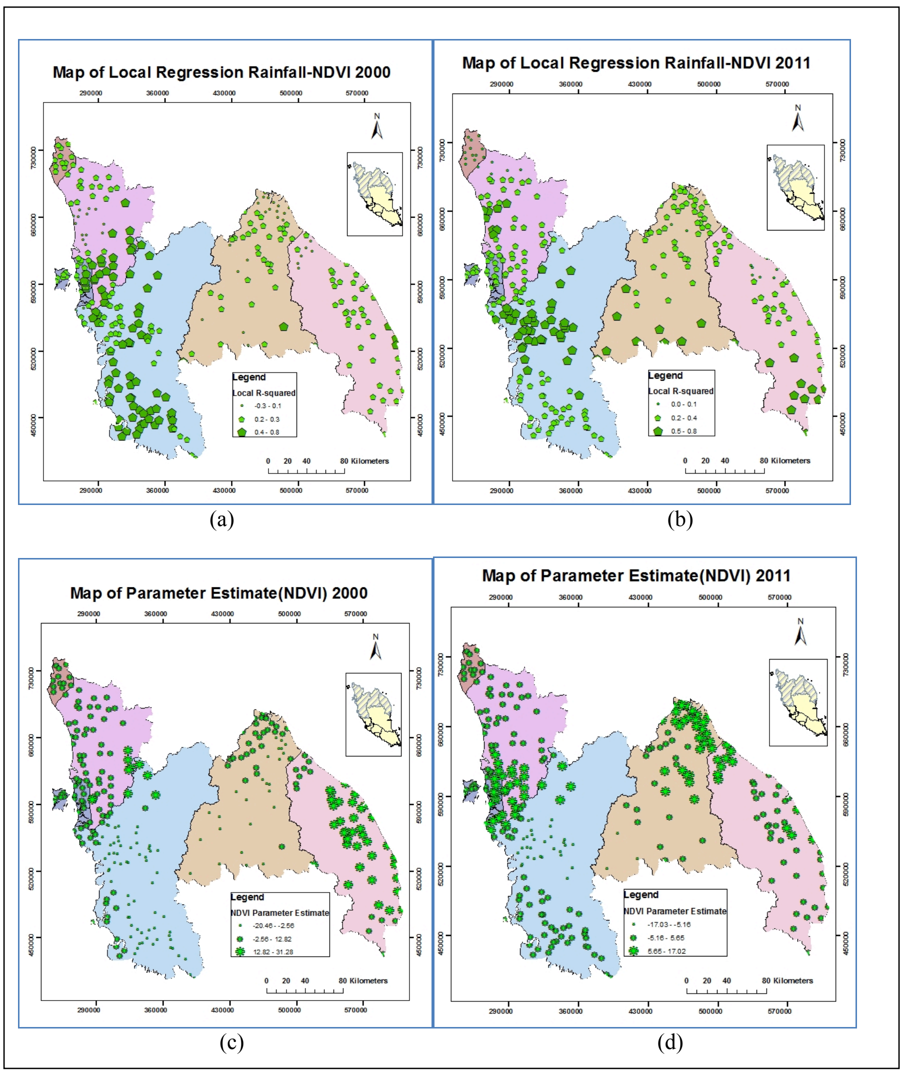


Figure 5. Maps of rainfall spatial variation in 2000 and 2001: (a) Rainfall-NDVI local regression in 2000; (b) Rainfall-NDVI local regression 2011; (c) NDVI estimated coefficient in 2000; and (d) NDVI estimated coefficient in 2011

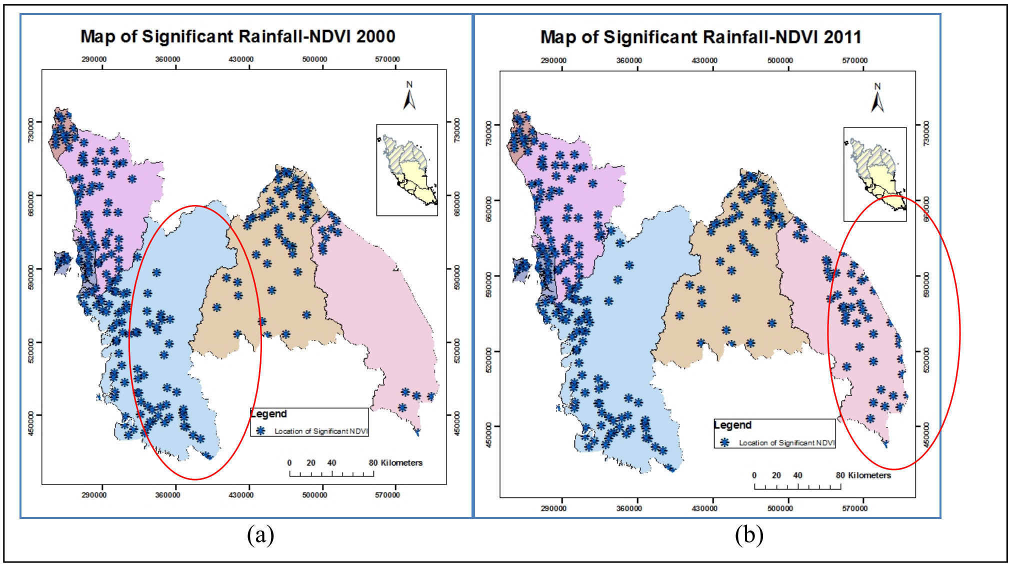


Figure 6. Significant maps based on t-value: (a) Significant rainfall-NDVI in 2000; and (b) Significant rainfall-NDVI in 2011

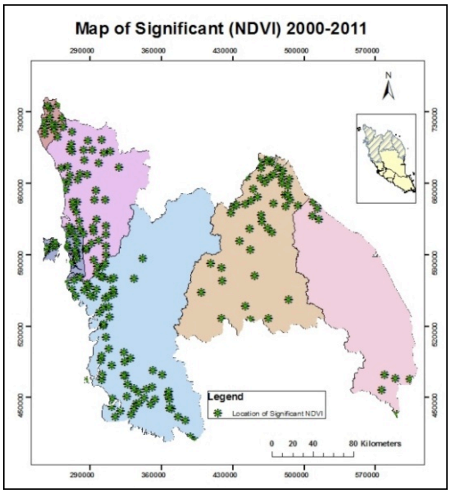


Figure 7. Map of significant locations of rainfall-NDVI for 2000 to 2011

CONCLUSION

Overall, this study has shown that rainfall spatial variation can be affected by surface characteristics such as vegetation. The findings support the evidence of heterogeneity of rainfall spatial variation, and the potential use of GWR to determine the spatial relationship between rainfall and vegetation. The use of remote sensing data from NDVI plays an important role in representing vegetation. The small clustering patterns of rainfall reveal the spatial non-stationarity and the existence of variation in rainfall. Thus, a spatial autocorrelation test of the variable such as applied by using Moran's I spatial autocorrelation is necessary to be implemented to prove the non-stationarity of the phenomenon and to support the findings of local regression. In the relationship between rainfall and vegetation, the exploration of the significant variation is possible to be carried out using the local approach of GWR. At global, the spatial variation of rainfall may not be identified since the R^2 of OLS was found to be extremely low. However, there is a variation of rainfall at a location when there is strong and significant GWR R^2. A realistic view of rainfall spatial variation can be depicted by local parameter estimation. The increase of the significant location in the rainfall-vegetation from 2000 to 2011 could be due to vegetation changes that affect rainfall variation in the study area while others indicated consistency in the rainfall-NDVI relationship. Thus, exploring the relationship between rainfall and vegetation at local scale reveals the impact of vegetation on rainfall spatial variation. Future work to investigate local relationship in rainfall spatial variation with combination of vegetation from NDVI and other earth surface characteristics needs to be done.

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REFERENCES

Ackerman, S. A., & Knox, J. A. (2011). *Meteorology: Understanding the atmosphere* (3rd ed.). Sudbury: Mass: Jones & Bartlett Learning.

Arnel, N. (2002). *Hydrology and global environmental change.* UK: Prentice Hall.

Avissar, D. R., & Werth. (2005). Global hydroclimatological teleconnections resulting from tropical deforestation. *Journal of Hydrometeorol, 6*, 134–145.

Brunsdon, C., Fotheringham, S., & Charlton, M. (1998). Geographically weighted regression. *Journal of the Royal Statistical Society: Series D (The Statistician), 47*(3), 431-443.

Dirmeyer, P. A., & Shukla, J. (1994) Albedo as a modulator of climate response to tropical deforestation, *Journal of Geophysical Research, 99*(10), 20–877.

Foody, G. M. (2003). Geographical weighting as a further refinement to regression modelling: An example focused on the NDVI-rainfall relationship. *Remote Sensing Environment, 88*, 283–293.

Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2002). *Geographically Weighted Regression: The analysis of spatial varying relationships*. Chichester: Wiley.

Georganos, S. (2016). *Exploring the spatial relationship between NDVI and rainfall in the semi-arid Sahel using geographically weighted regression* (Master Thesis), Lund University, Sweden.

Jackson, R. D., & Huete, A. R. (1991). Interpreting vegetation indices. *Preventive Veterinary Medicine, 11*, 185 - 200.

Kishtawal C. M., Niyogi, D., Tewari, M., Pielke, R. A., & Shepherd, J. M. (2010). Urbanization signature in the observed heavy rainfall climatology over India. *International Journal of Climatology, 30*(13), 1908–1916.

Lloyd, C. D. (2011). *Local Models for Spatial Analysis* (2nd ed.) CRC Press.

Lillesand, T., & Kiefer, R.W. (2004). *Remote Sensing and Image Interpretation*, (5th ed.). John Wiley, UK.

Matthews S. A., & Yang, T. C. (2012). Mapping the results of local statistics. *Demographic Research, 26*, 151–166.

Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika, 37*(1), 17–23.

Morie, N. D. (2007). *Land use and land cover changes in Harenna Forest, Bale Mountains National Park, Oromia National Regional State, Ethiopia* (Master Thesis), Addis Ababa University.

Nakaya, T., Fotheringham, A. S., Charlton, M., & Brundsdon, C. (2009). Semiparametric geographically weighted generalised linear modelling in GWR 4.0. *Proceedings of the 10th International Conference on GeoComputation*, Sydney. Retrieved from http://www.geocomputation.org/2009/PDF/Nakaya_et_al.pdf

Nicholson, S. E. (2000). The nature of rainfall variability over Africa on times scales of decades to millennia. *Global and Planetary Change, 26*, 137–158.

Propastin, P., Kappas, M., & Erasmi, S. (2008). Application of geographically weighted regression to investigate the impact of scale on prediction uncertainty by modelling relationship between vegetation and climate. *International Journal of Spatial Data Infrastructures, 3*, 73–94.

Shepherd J. M., & Mote T. L., (2009) Urban effects on rainfall variability: Potential implications for Georgia's water supply. *Proceedings of the 2009 Georgia Water Resources Conference* (pp. 253-258). The University of Georgia, Athens.

Tobler, A. W. R. (1970). A computer movie simulating urban growth in the detroit region. *Economic Geography, 46*, 234–240. doi:10.1126/science.11.277.620

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing Environment, 8*(2), 127–150.

Usman, U., Yelwa, S. A., Gulumbe, S. U., Danbaba, A., & Nir, R. (2013). Modelling relationship between NDVI and climatic variables using Geographically Weighted Regression. *Journal of Mathematical Sciences and Applications, 1*(2), 24–28. doi:10.12691/jmsa-1-2-2

Ward, A. D., & Trimble, S. W. (2004). *Environmental Hydrology*, (2nd ed.). Boca Raton: CRC Press.

Yuan, F., & Roy, S. S. (2007). Analysis of the relationship between NDVI and climate variables in Minnesota using Geographical Weighted Regression and spatial interpolation. *American Society for Photogrammetry and Remote Sensing - ASPRS Annual Conference 2007: Identifying Geospatial Solutions, 2*, 784-789.

Zhao, Z., Gao, J., & Wang, Y. (2014). Exploring spatially variable relationships between NDVI and climatic factors in a transition zone using geographically weighted regression. *Theoretical and Applied Climatology, 120*(3-4), 507-519. doi:10.1007/s00704-014-1188-x