Assessing the relationships between elevation and extreme precipitation with various durations in southern Taiwan using spatial regression models

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Abstract:
A spatially autocorrelated effect exists in precipitation of a mountainous basin. This study examines the relationship between maximum annual rainfall and elevation in the Kaoping River Basin of southern Taiwan using spatial regression models (i.e. geographically weighted regression (GWR), simultaneous autoregression (SAR), and conditional autoregression (CAR)). Results show that the GWR, SAR, and CAR models can improve spatial data fitting and provide an enhanced estimation for the rainfall–elevation relationship than the ordinary least squares approach. In particular, GWR achieves the most accurate estimation, and SAR and CAR achieve similar performance in terms of the Akaike information criterion. The relationship between extreme rainfall and elevation for longer duration is more concise than that for short durations. Results show that the spatial distribution of precipitation depends on elevation and that rainfall patterns in study area are heterogeneous between the southwestern plain and the eastern mountain area. Copyright © 2011 John Wiley & Sons, Ltd.

KEY WORDS extreme precipitation; elevation; geographically weighted regression (GWR); simultaneous autoregression (SAR); conditional autoregression (CAR)

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INTRODUCTION
Numerous studies investigate the relationship between precipitation and elevation (e.g. Basist et al., 1994; Harris et al., 1996; Guan et al., 2005; Allamano et al., 2009) and typically find a significant relationship. Precipitation amounts increase with elevation, and mountainous environments tend to exhibit more intense and frequent precipitations (Allamano, et al., 2009). The reason for increasing precipitation with elevation is orographic precipitation gradient, or orographic uplift, in which air masses are forced to rise by the relief of the land they pass over (Allamano et al., 2009). The orographic precipitation gradient is a crucial factor in hydrologic forecasting in mountain basins (Lundquist et al., 2010). Previous researches incorporated elevation to estimate spatial rainfall patterns using geostatistical approaches (Goovaerts, 2000; Guan et al., 2005; Lloyd, 2005). Daly et al. (1994, 2002) considered orographic effects and estimated monthly precipitation using the Parameter-Elevation Regressions on the Independent Slopes Model (PRISM). The PRISM defines monthly precipitation climatology through locally established empirical relationships between rainfall and elevation.

Several studies have applied spatial regression to environmental and ecological data such as rainfall and species distribution data (Brunsdon et al., 2001; Keitt et al., 2002; Lloyd, 2007; Kissling and Carl, 2008; Li et al. 2010). Because spatial autocorrelations of rainfall data are relatively common, they should be considered in a regression model. Brunsdon et al. (2001) used geographically weighted regression (GWR) to highlight rapid rainfall changes in the elevation coefficient across lowland England that were not apparent using traditional regressions. Thus, the GWR model has the advantage of solving the limitation of the traditional approaches. Lloyd (2007) applied the GWR and moving window regression to analyze the relationship between precipitation and elevation in Great Britain. The results of that study show that spatial regression as a function of distance from prediction location may increase prediction accuracy. Keitt et al. (2002) used several models, including simultaneous autoregression (SAR) and conditional autoregression (CAR), to model environment–abundance relationships in the presence of spatial autocorrelation. Kissling and Carl (2008) considered the performance of common ordinary least squares (OLS) and three different SAR models when accounting for spatial autocorrelation in species distribution data. Zhang et al. (2005) used six modeling techniques (i.e. OLS, GWR, linear mixed model, generalized additive model, multi-layer perceptron neural network, and a radial basis function neural network to model the relationships between tree crown area and diameter. Li et al. (2010) identified the relationships between land surface temperature and its explanatory variables using GWR and OLS. Their results show that the GWR model is an alternative approach to addressing spatial non-stationary and scale-dependent problems in ecology (Zhang et al. 2005; Li et al. 2010).
The current study uses the three different models (i.e. GWR, SAR, and CAR) to account for spatial autocorrelation in rainfall distribution datasets with known spatial properties. This study also investigates the existence of relationships between maximum precipitation and terrain for various durations in long-term planning.

MATERIAL AND STUDY AREA

Typhoon Morakot struck Taiwan from 7 August, 2009 to 9 August, 2009, causing extreme rainfall in southern Taiwan. The storm produced excessive rainfall, peaking at 2777 mm, surpassing the previous record of 1736 mm set by Typhoon Herb in 1996 (Ge et al., 2010). Typhoon Morakot wreaked catastrophic damage in Taiwan. The extreme amount of rainfall triggered enormous mudslides and severe flooding throughout southern Taiwan. This study analyzes rainfall data collected from 41 stations in the Kaoping River Basin between 1982 and 2010. The maximum rainfall occurred during Typhoon Morakot (2009). Spatial regression models were used to incorporate elevation into the mapping of the extreme rainfall in the study area.

The Kaoping River Basin is located near the southwestern foothills in Taiwan (Figure 1). The Kaoping River, with a length of 171 km, is the largest river in Taiwan for drainage area (3257 km²), and the estimated mean annual runoff is $8.45 \times 10^9$ m³. The headwater of the river originates in the southern part of the Central Mountain Range near Jade Mountain, of which the elevation is 3997 m above sea level. In this area, 47.45% of the drainage basin is above 1000 m; 32.38% is between 100 and 1000 m; and 20.17% is below 100 m.

METHOD

This study attempts to (1) identify the descriptive statistics and relationships between the elevation and extreme precipitation with various durations in the study area; (2) build traditional OLS and spatial regression models such as GWR, SAR, and CAR to determine the elevation–extreme precipitation relationship; (3) assess the model performance in terms of the AIC and adjusted $r^2$ and identify the best model in this case study; and (4) determine Moran’s I of the model residuals of extreme precipitations at various durations and validate the model accounting for spatial autocorrelation of data.

Geographically weighted regression (GWR)

The GWR technique extends the conventional global regression by adding a geographical location parameter, with the model rewritten as:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \epsilon_i$$  \hspace{1cm} (1)

where $y_i$, $x_{ik}$, and $\epsilon_i$ represent the response (dependent) variable, the predictor (independent) variables, and random error term at spatial points $i$. $\beta_0(u_i, v_i)$ is the model intercept, and $\beta_k(u_i, v_i)$ is the slope coefficient for $k$th predictor variable at the coordinates of the $i$th point at $(u_i, v_i)$.

To estimate the parameters in Equation (1), an observation is weighted according to its proximity to a specific point $i$, i.e. the distance between observation and point $i$ determines the weight given to the observation; larger weights are assigned to observations closer to point $i$. Therefore, the weighting of an observation in the analysis is not constant, but is a function of geographical location.
The parameters in Equation (1) could be estimated by solving the following matrix equation:

$$\hat{\beta}(u_i, v_i) = (X^TW(u_i, v_i)X)^{-1}X^TW(u_i, v_i)Y$$  \hspace{1cm} (2)

where \(\hat{\beta}(u_i, v_i)\) represents the unbiased estimate of \(\beta\), and \(W(u_i, v_i)\) is the weighting matrix, whose role is to ensure that observations near to the specific location have larger weight. In this study, the following Gaussian weighting kernel function form is used:

$$w_{ij} = \exp\left( -\frac{d_{ij}^2}{b^2} \right)$$  \hspace{1cm} (3)

where \(d_{ij}\) is the Euclidean distance between regression point \(i\) and neighboring observation \(j\), and \(b\) represents a bandwidth of the kernel function. In Equation (3), if \(j\) coincides with \(i\), the weighting value of the data at that point is set to 1, while \(w_{ij}\) decreases according to a Gaussian curve as the distance \((d_{ij})\) increases (Fotheringham et al., 2002; Shi et al., 2006; Li et al., 2010).

**Simultaneous autoregressive (SAR)**

Simultaneous autoregressive (SAR) models can take different forms, depending on where the spatial autoregressive process is believed to occur (Cliff and Ord 1981; Anselin, 1988; Haining, 2003; Kissling and Carl, 2008). The SAR assume that the response at each location \(i\) is a function not only of the explanatory variable at \(i\), but of the values of the response at neighboring locations \(j\) as well. The neighborhood relationship is formally expressed in spatial weights \((W)\) representing a measure of the connection (i.e. geographical distance) between locations \(i\) and \(j\). The first SAR model (lagged-response model) assumes that the autoregressive process only generates in the response variable, and thus includes a term \((\rho W)\) for the spatial autocorrelation in the response variable \(Y\), but also the standard term for the predictors and errors \((X\beta + \varepsilon)\) as used in an OLS regression. The SAR lagged-response model takes the form:

$$Y = X\beta + \rho WY + \varepsilon$$  \hspace{1cm} (4)

where \(\rho\) is the autoregressive parameter, \(W\) is the spatial weights matrix, and \(\hat{\beta}\) is a vector representing the slopes associated with the predictors in the original predictor matrix \((X)\). Second, the 'spatial error model' assumes that the autoregressive process occurs only in the error term and neither in response nor in predictor variables. The model is most similar to the CAR, with no directionality in the error (Kissling and Carl, 2008). Third, 'lagged-mixed model' is that spatial autocorrelation can affect both response and predictor variables (Kissling and Carl, 2008). In the study, the lagged-response model is used as the SAR model.

**Conditional autoregression (CAR)**

The CAR model can be written as (Keitt et al. 2002; Kissling and Carl, 2008):

$$Y = X\beta + \rho W(Y - X\beta) + \varepsilon$$  \hspace{1cm} (5)

The direct computation of other forms of spatial regressions such as SAR and CAR are allowed by the generalized least squares framework (Lichstein et al., 2002; Dark, 2004; Tognelli and Kelt, 2004, Rangel et al., 2006) that computes the matrix \(C\) with different formats. For the SAR, the covariance matrix among residuals is given by:

$$C = \sigma^2 \left[(I - \rho W)^T(I - \rho W)\right]^{-1}$$  \hspace{1cm} (6)

where \(\sigma^2\) is the variance of the residuals, and \(I\) is an \(n \times n\) identity matrix. For the CAR, this matrix is given as (Keitt et al., 2002):

$$C = \sigma^2 (I - \rho W)^{-1}$$  \hspace{1cm} (7)

From the both models, \(C\) is the function only of autoregressive parameter \((\rho)\) and spatial weights matrix \((W)\), where \(W\) has to be symmetric, as an inverse function of geographic distances in the study. The model form leads us that the CAR is similar to SAR. However, the CAR model only considers first-order neighborhood effects, whereas the SAR model allows for recursive and higher order neighborhood effects (Keitt et al., 2002). In the study, spatial regressions such as the CAR, SAR, and GWR were performed by the SAM 4.0 (Spatial Analysis in Macroecology) statistical tool (Rangel et al., 2006).

**Moran’s I**

Moran’s I is a useful tool for describing the dependency of spatial patterns or spatial autocorrelation of data. The study uses Moran’s I to assess the spatial autocorrelation of model residuals. Moran’s I, which ranges between -1 and +1, is a well-known spatial autocorrelation method. The index, \(I\), is calculated as follows (Moran, 1950):

$$I = \frac{(1/WT)\sum_{j=1}^{n} \sum_{k=1}^{n} w_{jk} (z_j - \bar{z})(z_k - \bar{z})}{(1/n) \sum_{j=1}^{n} (z_j - \bar{z})^2},$$  \hspace{1cm} (8)

where \(z_j\) and \(z_k\) denote the values of the observed variable (i.e. elevation, rainfall, and model residual in the study) at sites \(j\) and \(k\), respectively; and \(w_{jk}\) denotes the weight of the variable. The \((n \times n)\) weight matrix \(WT\), is the sum of the weights \(w_{jk}\) for a given distance class. Moran’s I is high and positive when a value is similar to adjacent values but low when one is dissimilar to adjacent values. A zero value of Moran’s I indicates a random spatial pattern.

**RESULTS**

**Relationship between extreme rainfall and elevation**

Table I shows descriptive statistics of elevation and extreme rainfall at various durations. The elevation of the study area varies from 24 to 2700 m, and the mean
extreme rainfall volumes at 1-, 3-, 6-, 12-, and 24-h duration range from 86 to 947 mm. Table II shows the cross-correlation coefficients between elevation and extreme rainfall records at 1, 3, 6, 12, and 24 h. These results imply that the correlation increases in conjunction with rainfall duration, and the highest correlation appears at 24 h (i.e. 0.659). The correlation between rainfall and elevation for longer durations (i.e. 12–24 h) is higher than that for short durations. Figure 2 shows the x-y plot of elevation and rainfall at various durations. Results show that the relationship between extreme rainfall and elevation between 200 and 1700 m is nonlinear, that is, rainfall varies significantly with elevation. Figure 3 shows spatial autocorrelations of elevation and precipitation at various durations in Moran’s I curves. The gradient spatial patterns of elevation in the study area exhibit positive spatial autocorrelation values at short distances (i.e. under 37 km) but negative values above 37 km. At durations of 3, 6, 12, and 24 h, Moran’s I of rainfall is

Table I. Descriptive statistics of elevation (m) and extreme rainfalls at various durations (mm)

<table>
<thead>
<tr>
<th></th>
<th>Elevation</th>
<th>1 h</th>
<th>3 h</th>
<th>6 h</th>
<th>12 h</th>
<th>24 h</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>697</td>
<td>86</td>
<td>200</td>
<td>348</td>
<td>585</td>
<td>947</td>
</tr>
<tr>
<td>SD</td>
<td>764</td>
<td>20</td>
<td>67</td>
<td>109</td>
<td>191</td>
<td>296</td>
</tr>
<tr>
<td>Q25</td>
<td>64</td>
<td>71</td>
<td>147</td>
<td>249</td>
<td>416</td>
<td>683</td>
</tr>
<tr>
<td>Q75</td>
<td>1018</td>
<td>99</td>
<td>252</td>
<td>433</td>
<td>727</td>
<td>1195</td>
</tr>
<tr>
<td>Min</td>
<td>24</td>
<td>48</td>
<td>91</td>
<td>151</td>
<td>197</td>
<td>338</td>
</tr>
<tr>
<td>Max</td>
<td>2700</td>
<td>130</td>
<td>375</td>
<td>557</td>
<td>872</td>
<td>1449</td>
</tr>
</tbody>
</table>

SD: standard deviation; Q25: the first quartile; Q75: the third quartile; Min: minimum; Max: maximum

Table II. Correlation coefficients between elevation and extreme rainfalls at various durations

<table>
<thead>
<tr>
<th></th>
<th>1 h</th>
<th>3 h</th>
<th>6 h</th>
<th>12 h</th>
<th>24 h</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pearson’s correlation</td>
<td>0.155</td>
<td>0.384</td>
<td>0.478</td>
<td>0.582</td>
<td>0.659</td>
</tr>
</tbody>
</table>

Figure 2. Relationship between elevation and extreme precipitation at various durations of (a) 1 h (b) 3 h (c) 6 h (d) 12 h (e) 24 h
Spatial regression model performance

Table III shows the performance of OLS and three spatial regression models (GWR, SAR, and CAR). The Akaike information criterion (AIC) is a statistical criterion of the relative goodness of fit, and the AIC approximation is based on likelihood under a normal distribution of error terms (Mangel and Hilborne, 1997; Rangel et al., 2006). This study uses the AIC to determine the performance of spatial regression model. The most accurate model has the smallest AIC. Results show that the largest AIC model is the OLS and implies that traditional regression performs poorly because the rainfall depends on spatial allocation. The smallest AIC model is the GWR, and the SAR and CAR models produce similar AIC values. Results show that the GWR is superior to the other two spatial regression models and the OLS. The GWR provides the most accurate estimations for the response variable. The adjusted $r^2$ values are greater than 0.7 in the GWR and between 0.3 and 0.5 in the SAR and CAR, except at 1-h duration. Table IV shows the coefficients of various models.

Figure 4 shows the GWR rainfall estimation and observation at various durations. The correlation coefficients between GWR estimation and observation are 0.73, 0.89, 0.90, 0.92, and 0.90 at durations of 1, 3, 6, 12, and 24 h, respectively. Compared to various duration rainfall estimations, this result matches the GWR model performance in AIC and adjusted $r^2$, indicating that longer durations are better than short durations (Table III). Furthermore, Moran’s I of model residuals is a measurement of goodness of fit in the spatial regression (Zhang et al., 2005; Kissling and Carl, 2008; Beale et al., 2010). Figure 5 shows Moran’s I of the GWR model residual at various durations. This study uses the Moran coefficient to investigate the spatial distribution and heterogeneity of GWR model residuals. Results show that Moran’s I is approximately zero when the model residuals are arranged randomly and independently over space. This indicates that the GWR model is able to account for the spatial autocorrelation of the data.

Spatial patterns of estimated rainfall at various durations

Figure 6 shows estimated spatial maps of extreme rainfall at various durations using GWR. Extreme rainfall estimation is significantly related to elevation as duration increases. Rainfall usually increases with elevation in mountainous areas, except for 1-h duration. Because the relationship between 1-h rainfall and elevation is unclear, the spatial distribution of the estimated 1-h rainfall is associated with lowland and the watershed channel. However, extreme rainfall estimation maps reveal heterogeneous areas in the plain and mountain areas. Extreme 1-h rainfall varies between 40 and 80 mm at the southwest and northeast of the study area and between 80 and 130 mm at the eastern border. Extreme 3-h, 6-h, and 12-h rainfall events at the southwest plain are under 180, 300, and 500 mm, and are 180 ~ 421, 300 ~ 833, and

**Table III. Performance comparison between OLS and three spatial regression models (i.e. GWR, SAR, and CAR)**

<table>
<thead>
<tr>
<th>Model</th>
<th>Duration</th>
<th>AIC</th>
<th>Adjusted $r^2$</th>
<th>P-value ($r^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td>1 h</td>
<td>371.6</td>
<td>0.024</td>
<td>0.623</td>
</tr>
<tr>
<td></td>
<td>3 h</td>
<td>463.8</td>
<td>0.147</td>
<td>0.046</td>
</tr>
<tr>
<td></td>
<td>6 h</td>
<td>499.8</td>
<td>0.228</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>12 h</td>
<td>539.3</td>
<td>0.338</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td>24 h</td>
<td>568.7</td>
<td>0.435</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>GWR</td>
<td>1 h</td>
<td>355.8</td>
<td>0.453</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td>3 h</td>
<td>421.9</td>
<td>0.750</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td>6 h</td>
<td>455.8</td>
<td>0.782</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td>12 h</td>
<td>492.7</td>
<td>0.823</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td>24 h</td>
<td>538.5</td>
<td>0.774</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>SAR</td>
<td>1 h</td>
<td>355.8</td>
<td>0.337</td>
<td>0.926</td>
</tr>
<tr>
<td></td>
<td>3 h</td>
<td>453.8</td>
<td>0.332</td>
<td>0.039</td>
</tr>
<tr>
<td></td>
<td>6 h</td>
<td>490.5</td>
<td>0.384</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td>12 h</td>
<td>532.1</td>
<td>0.445</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td>24 h</td>
<td>564.9</td>
<td>0.484</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>CAR</td>
<td>1 h</td>
<td>364.0</td>
<td>0.188</td>
<td>0.336</td>
</tr>
<tr>
<td></td>
<td>3 h</td>
<td>456.2</td>
<td>0.292</td>
<td>0.014</td>
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<tr>
<td></td>
<td>6 h</td>
<td>492.5</td>
<td>0.354</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>12 h</td>
<td>533.5</td>
<td>0.426</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td>24 h</td>
<td>562.9</td>
<td>0.509</td>
<td>&lt;.001</td>
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<table>
<thead>
<tr>
<th>Model</th>
<th>Coefficient</th>
<th>OLS</th>
<th>GWR</th>
<th>SAR</th>
<th>CAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 h</td>
<td>Intercept</td>
<td>83.024</td>
<td>79.112</td>
<td>91.1</td>
<td>83.688</td>
</tr>
<tr>
<td></td>
<td>Slope</td>
<td>0.004</td>
<td>0.016</td>
<td>&lt;.001</td>
<td>0.005</td>
</tr>
<tr>
<td>3 h</td>
<td>Intercept</td>
<td>176.816</td>
<td>149.254</td>
<td>193.053</td>
<td>183.407</td>
</tr>
<tr>
<td></td>
<td>Slope</td>
<td>0.034</td>
<td>0.067</td>
<td>0.016</td>
<td>0.031</td>
</tr>
<tr>
<td>6 h</td>
<td>Intercept</td>
<td>360.342</td>
<td>251.324</td>
<td>324.628</td>
<td>304.365</td>
</tr>
<tr>
<td></td>
<td>Slope</td>
<td>0.068</td>
<td>0.167</td>
<td>0.05</td>
<td>0.069</td>
</tr>
<tr>
<td>12 h</td>
<td>Intercept</td>
<td>483.147</td>
<td>398.786</td>
<td>551.712</td>
<td>480.893</td>
</tr>
<tr>
<td></td>
<td>Slope</td>
<td>0.146</td>
<td>0.252</td>
<td>0.117</td>
<td>0.155</td>
</tr>
<tr>
<td>24 h</td>
<td>Intercept</td>
<td>769.053</td>
<td>676.113</td>
<td>839.097</td>
<td>758.74</td>
</tr>
<tr>
<td></td>
<td>Slope</td>
<td>0.256</td>
<td>0.474</td>
<td>0.226</td>
<td>0.283</td>
</tr>
</tbody>
</table>

a: Akaike information criterion; b: Adjusted $r^2$ adjusts $r^2$ for the added degrees of freedom and can be used to compare models that consider various parameter numbers.

d: the median of model coefficients in GWR.
500~1737 mm surrounded by mountain areas over the northeast and along the eastern border, respectively. Over most of the southwest plain of the study area, the elevation ranges from 0 to 470 m, and extreme 24-h rainfall remains under 800 mm. Extreme 24-h rainfalls are 800 to 2171 mm surrounded by mountain ranges along the eastern and northeast border, where the elevations are close to 3000 m. Because the central mountain range has an elevation of up to 4 km, the distribution of rainfall in Taiwan associated with typhoons depends not only on the distribution of typhoon internal structure and the monsoon-scale environmental flow, but also on orographic effects (Cheung et al., 2008).

DISCUSSION

Researchers typically use OLS regression analysis to derive a relationship for uniform cases across a study area. In the real world, this approach may provide an inappropriate description of the relationship between variables. Failure to account for spatial autocorrelation...
can lead to incorrect conclusions in environmental problems (Keitt et al., 2002). In recent years, there has been increasing interest in regression techniques that account for spatial autocorrelations among data observations (Keitt et al., 2002; Zhang et al., 2005; Kissling and Carl, 2008; Beale et al., 2010). Clearly, precipitation patterns vary by location. This study uses spatial regression models, and especially the GWR, to examine the effects of local spatial heterogeneity on precipitation. In contrast, the SAR and CAR consider the additional spatial term that is implemented with the weight of each neighbor. The GWR explicitly considers spatial-dependence parameters and estimates model parameters at each location in the study area. The results of this study agree with those of previous researches in showing that the GWR produces more accurate predictions for the response variable (Zhang et al., 2005; Li et al., 2010). The GWR model can estimate regression coefficients at any spatial location. Therefore, the residuals of the GWR model have more desirable spatial randomness than those derived from other models (Zhang et al., 2005; Li et al., 2010).

Heavy rain often triggers widespread landslides in Taiwan. Rainfall over a long duration is usually a cause of landslides. Compared to the goodness-of-fit values at various durations, the AIC and adjusted $r^2$ are superior for longer duration than short durations. Therefore, the rainfall–elevation relationship can improve rainfall pattern estimation for landslide monitoring and serve as a landslide warning threshold during a typhoon or long duration rainfall. Results also show that the orographic effect increases precipitation with elevation in the Kaoping River Basin of southern Taiwan. Previous research suggests that using elevation as a vital variable in rainfall estimation increases the accuracy of estimation in most locations (Lloyd, 2005). Precipitation generally increases with elevation. However, the spatial pattern of precipitation is highly dependent on meteorological conditions.
conditions and relief of mountain ranges. The relationship between precipitation and topography in mountainous areas remains unclear (Goovaerts, 2000). Future studies should investigate whether other meteorological variables, such as wind orientation, help explain the spatial variability of precipitation. This would help predict extreme rainfall at ungauged sites by applying a relationship based on the spatial regression at gauged sites.

CONCLUSION

Extreme rainfall analysis based on 41 observations from southern Taiwan during Typhoon Morakot is essential for future hazard management. This study uses spatial regression models (i.e. GWR, SAR, and CAR) to explore the spatial non-stationary relationships between elevation and extreme rainfall at various durations. Results indicate that the proposed model performs better for long durations than short durations. The SAR and CAR provide better estimations of extreme rainfall than the OLS model can, improving on OLS performance. The GWR produces more desirable spatial distribution for the model residuals and more accurate estimations than the other methods do.

One of the most valuable features of analysis is to identify the relationship between elevation and extreme rainfall at various durations. Extreme rainfall in the study area is heterogeneous in east mountain and southwest plain areas. This analysis shows that the orographic effect increases precipitation with elevation in the Kaoping River Basin of southern Taiwan. Terrain plays a primary role in extreme rainfall fluctuation in the study area. The rainfall—elevation relationship at long rainfall durations can help improve rainfall pattern estimation for a landslide warning system. Further investigation will confirm this approach of regional rainfall estimation by considering atmospheric effects such as atmospheric moisture and moisture flux direction.

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