SPATIAL DOWNSCALING FOR GLOBAL PRECIPITATION MEASUREMENT USING A GEOGRAPHICALLY AND TEMPORALLY WEIGHTED REGRESSION MODEL

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ABSTRACT

High-resolution precipitation data are crucial to monitor disasters in urban areas, especially in cases with abundant precipitation. Based on the spatiotemporal, non-stationary relationship between precipitation and normalized differential vegetation index (NDVI), in this paper we introduce a geographically and temporally weighted regression (GTWR) model and further evaluate it in a case study in Guangdong province, China, in the summer of 2015. Our results indicate that there is a mainly negative correlation between precipitation and NDVI in the summer. Our GTWR downscaling model performs better than a previously available geographically weighted regression (GWR) model, providing more accurate downscaled precipitation estimations. This suggests that considering the spatiotemporal, non-stationarity relationship between NDVI and precipitation, our GTWR downscaling model can provide high-spatial resolution precipitation estimates, with more details in urban areas with abundant precipitation.

Index Terms— Global precipitation measurement (GPM), geographically and temporally weighted regression (GTWR) model, normalized differential vegetation index (NDVI).

1. INTRODUCTION

Due to global warming, precipitation exhibits obvious temporal and spatial changes, and has a significant impact on the ecological environment [1]. Especially in urban areas with abundant precipitation, accurate estimates of precipitation are crucial to the monitoring of flood disasters [2]. Several satellite precipitation datasets have been developed to provide global estimations of precipitation. Compared with the precipitation data produced by interpolating the rain gauge observations, the satellite data are more reliable and accurate [3]. Guangdong province is located in the south coast of China, and the precipitation in this area is mainly concentrated from May to September [4]. As a result, this region faces a high risk of flood disasters. Moreover, the Pearl River Delta region (located in the central Guangdong province) is one of the most developed economic regions in China. The flood disasters caused by precipitation pose a huge threat to the regional economy and personal safety. Research on regional hydrometeorology and disasters have attracted great attention, and higher accuracy and finer spatial resolution precipitation data are highly required. Since precipitation within a region may occur at finer scales compared with the pixel size of satellites [5], satellite precipitation data needs to be downscaled properly to provide accurate and high-spatial resolution estimates of precipitation over Guangdong province.

Statistical downscaling methods allow modeling the relationship between precipitation and auxiliary high resolution data (e.g., vegetation index [6], elevation [7] and cloud properties) at large scale, and applying it to the regional scale in order to obtain downscaled results. For instance, the method in [8] constructed a tropical rainfall measuring mission (TRMM) precipitation downscaling model in humid tropical regions by using the site-specific seasonal coefficient. However, the obtained prediction accuracy was not ideal. Numerous methods, such as probability-matching [9] or machine learning [10] have been introduced into statistical downscaling models, and the non-stationary relationship between precipitation and surface characteristic factors has attracted more attention. The downscaled results based on a geographically weighted regression (GWR) model performed well in different regions [11]. However, recent research shows that, in areas with abundant precipitation, there is a lagging response of vegetation to precipitation. Huang et al. [12] introduced the time effect into the GWR model, and established a geographic spatial-temporal weighted regression model to deal with both spatial and temporal non-stationarity simultaneously in real-estate market data. It has been shown that the GTWR model can account for spatial and temporal variability in the relationship between variables [13]. However, there has been little focus on statistical downscaling in regions with heavy precipitation, in which the results have not been satisfactory.

In this paper, we introduce a geographically and temporally weighted regression (GTWR) model and further evaluate it in a case study in Guangdong province, China, in the summer of 2015, a case study with abundant precipitation. Our results indicate that the newly proposed GTWR downscaling model performs better than the previously available GWR model, providing more accurate downscaled precipitation estimations.

2. STUDY AREA AND DATA

2.1. Study area

Our study area, Guangdong province (109°45′E-117°20′E, 20°09′N-25°31′N), is located in the southern coast of China (Fig. 1). Guangdong is the most populated and developed province in China. The Pearl River Delta, located in the central and southern region of Guangdong, is one of the most developed urban agglomerations in China. The average temperature ranges from 19°C to 24°C, and the mean annual precipitation ranges from 1300*mm* to 2500*mm*.

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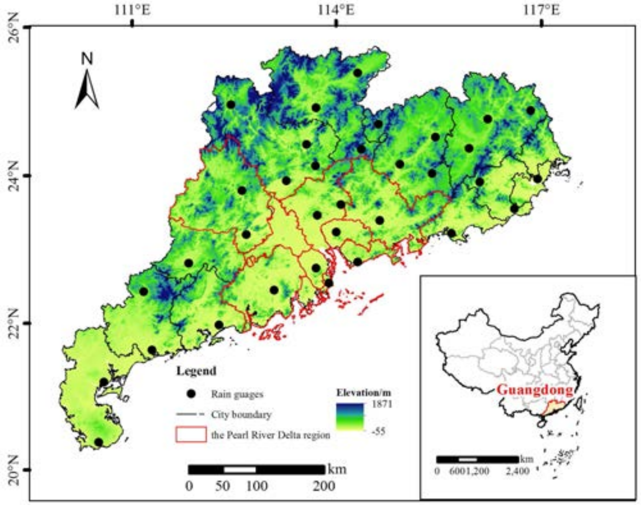

Fig. 1. Map of Guangdong province, indicating the location of rain gauges.

The spatial distribution of precipitation tends to be higher in the south and lower in the north, while the precipitation in the flood season from April to September accounts for more than 80% of the precipitation of the whole year.

2.2. Data

2.2.1. GPM precipitation data

The Global Precipitation Measurement (GPM) mission is an international network of satellites that provide the next-generation global observations of rain and snow. The level 3 data of GPM (GPM IMERG) can provide 1 day, 3 day, 7 day and monthly temporal resolution data from year 2000 to present. In this study, the GPM IMERG V05B 0.1° 1 day precipitation data are first downloaded[1], and then accumulated to 16-day data in order to match the temporal resolution of the available normalized differential vegetation index (NDVI) data.

2.2.2. NDVI data

The NDVI data are first obtained[2]. Specifically, the MOD13A2 dataset is downloaded from LAADS DAAC and provides 16-day vegetation indices data.

2.2.3. Rain gauge data

Daily precipitation collected from 34 rain gauge stations is downloaded from the National Meteorological Information Center in China[3]. The 16-day precipitation derived from rain gauges is generated by accumulating daily datasets. Fig. 1 shows the spatial distribution of rain gauge stations in the study area.

[1]ftp://arthurhou.pps.eosdis.nasa.gov/gpmdata
[2]https://lads-web.modaps.eosdis.nasa.gov
[3]http://data.cma.cn

3. METHODOLOGY

3.1. GTWR model

Our geographically and temporally weighted regression (GTWR) model can capture spatiotemporal heterogeneity based on a weighting matrix referencing both spatial and temporal dimensions [14]. In this study, the GTWR model has been enhanced to address the relationship between precipitation and NDVI. Adaptive bandwidths have been been used, where bandwidths are obtained by minimizing the corrected Akaike information criterion values [13]. Our model structure can be expressed as follows [12]:

$$P_i = \beta_0(\mu_i, \nu_i, t_i) + \beta_1(\mu_i, \nu_i, t_i) \times \mathrm{NDVI}_i + \varepsilon_i, \qquad (1)$$

where P_i is the precipitation of the sample i at location (μ_i, ν_i) on time stamp t_i at 16-day scale; β_0 denotes the intersection at a specific location (μ_i, ν_i) on time stamp t_i; and β_1 is the location time-specific slope for lag adjusted NDVI. The location (μ_i, ν_i) represents the central coordinate of a grid cell in which sample i is located. t_i is the time stamp, and only the estimation for that time and the previous time ($t_i < t_{estimation}$) are used for modeling. Finally, ε_i is the error term for sample i.

The GTWR model has been established based on precipitation and lag adjusted NDVI at sparse resolution. Then, the model parameters are resampled to 1km, and the residuals are interpolated to 1km by using a spline tensor interpolator. All of these are applied to the 1km lag-adjusted NDVI to obtain the 1km GTWR downscaled precipitation results.

3.2. NDVI lag analysis

Correlation coefficients between precipitation and NDVI are calculated by using the Pearson correlation coefficient. The relationship between precipitation and NDVI for the corresponding period and the following three months are analyzed. The lag phase is determined according to the maximum correlation coefficient between the precipitation and NDVI in different periods.

3.3. Validation

To evaluate the performance of our GTWR, the downscaling model based on GWR at 16-day time scale has been established for comparison. The correlation coefficient (r), mean absolute error (MAE), root mean square error (RMSE), and bias are calculated to assess the accuracy of the downscaled precipitation and GPM precipitation, while the rain gauge data is seen as the true value.

4. EXPERIMENTAL RESULTS

4.1. Relationship between precipitation and NDVI

The relationship between precipitation and NDVI has been analyzed at the considered 16-day time scale. Fig. 2 shows the lag-phase of the response of NDVI to precipitation and the maximum correlation coefficients. There are mainly no lag responses in the central area, and 1 to 2 months responses in the other areas. Meanwhile, we observed mainly negative correlation between precipitation and NDVI, and the absolute values of the correlation coefficient are relatively large. In general, the relationship between precipitation and NDVI at the considered 16-day time scale is sufficient to be used in GTWR downscaling model.

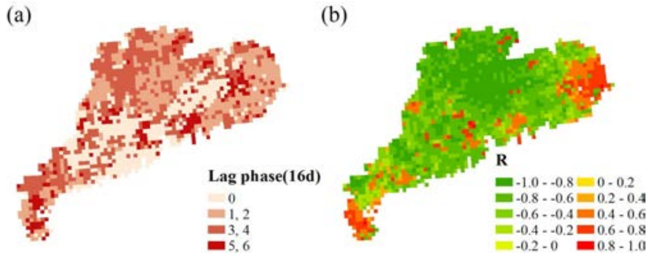

Fig. 2. (a) Lag-phase of NDVI response to precipitation and maximum correlation coefficient in Guandong province, summer of 2015. (b) Accumulated results (from day 145 to day 240).

4.2. Accuracy of downscaled precipitation

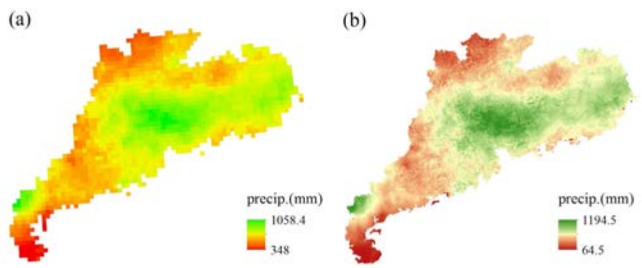

Fig. 3. (a) Accumulated GPM precipitation. (b) Accumulated GTWR downscaling results (from day 145 to day 240) in 2015.

The GTWR model has been applied based on the relationship between precipitation and lag-adjusted NDVI at the considered 16-day scale. The downscaled results are shown in Figs. 3 and 4, and the validation of the results is presented in Table 1. Specifically, Fig. 3 presents the accumulated GPM data and the downscaled results. The GTWR downscaled result exhibits a similar spatial distribution with regards to the original GPM data of precipitation, providing more spatial details. The maximum precipitation exceeded 1000mm in the summer of 2015, and the higher values of total precipitation are concentrated in the central and southern regions, covering the Pearl River Delta. Fig. 4 presents the GPM data and the downscaled results in the Pearl River Delta. Compared to the GPM data, the GTWR downscaled results show more details and a better representation of the precipitation distribution for monitoring of floods in the urban area. We can see that the extreme precipitation events occur in the period from day 193 to day 208.

Table 1 shows the validation of original GPM data, GWR and GTWR downscaled results against ground observations from 34 rain gauges on the Guangdong province. The accuracy of GPM data in the period from day 177, 209 and 225 decreases significantly, with r values of 0.55, 0.45 and 0.57, overestimating the precipitation in the period from day 177 and underestimating it in the period from day 209. This is mainly because of the heavy rainfall in the period from day 193. The GTWR model results exhibit a higher value of r and lower error values than those obtained by GWR results in most of the considered days. Specifically, The overall performance of GTWR model is better than that of the GWR model. In the period from days 177 and 209, although the error values of the original GPM data are higher, the error values of GTWR results decreased due to the use of data from previous periods. In the other tested times, the value of r and the errors are close to those obtained by the original GPM. However, in the period from day 193 and 209, the accuracy of model results are relatively poor compared to the GPM data. This is mainly because of the extreme precipitation event happening those days. In general, our results show that the GTWR model performs well at the considered 16-day time scale, with a significant improvement in the spatial resolution of GTWR downscaled results.

5. CONCLUSIONS AND FUTURE WORK

Based on the analysis of the relationship between NDVI and precipitation, a GTWR downscaling model has been established to obtain high spatial resolution precipitation data in areas with abundant precipitation. Our model has been validated by a downscaling experiment in Guangdong province in the summer of 2015, demonstrating that the newly proposed GTWR can provide a high spatial resolution precipitation estimates, with detailed information at the considered 16-day time scale. It has been found that the performance of our GTWR model is better than that of a previously available GWR model, and the obtained results are close to the original GPM data. In the future, additional land surface characteristics and data from meteorological stations will be introduced in the considered downscaling model.

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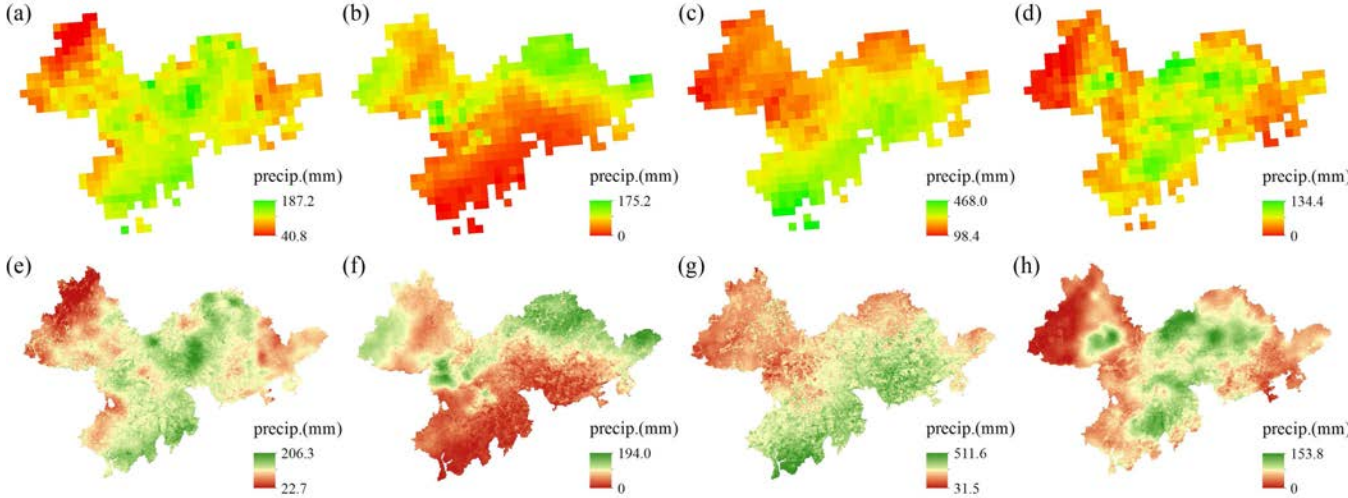

Fig. 4. (a)-(d) 16-day GPM precipitation in the period from day 161, 177, 193 and 209, respectively, (e)-(h) 16-day GTWR downscaled results at the corresponding periods in 2015.

Table 1. Correlation coefficient (r), bias and root mean square error (RMSE) for the original GPM data and the downscaled results based on GTWR, compared with the ground rain gauge observations in the summer of 2015 at 16-day scale.

16 day	R			BIAS(%)			MAE			RMSE		
	GPM	GWR	GTWR	GPM	GWR	GTWR	GPM	GWR	GTWR	GPM	GWR	GTWR
2015145	0.75	0.75	0.75	7.36	14.65	9.47	22.78	23.69	23.14	41.86	44.19	42.47
2015161	0.75	0.55	0.71	5.74	5.32	10.06	11.32	12.78	13.24	20.54	24.93	22.88
2015177	0.55	0.56	0.55	16.39	24.48	11.50	19.93	19.94	18.97	36.32	35.85	34.72
2015193	0.70	0.64	0.63	4.26	4.80	9.90	26.75	29.17	30.68	46.84	51.55	56.88
2015209	0.45	0.40	0.36	-9.91	-13.47	-5.65	13.89	15.14	14.21	25.29	27.51	27.29
2015225	0.59	0.51	0.57	1.97	4.04	3.04	18.92	20.53	19.45	33.94	36.34	34.51

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