

Analysis the Impact of Drought on NDVI in Drought Periods Combined with Climate factors and Land Cover in Southwest China

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Abstract - From winter 2009 to spring 2010, due to decreasing precipitation and high temperature, Southwest China experienced the worst meteorological drought in 60 years. The drought has impacted large areas of Guizhou, Yunnan, Guangxi and Sichuan provinces. In this paper, climate data (precipitation and temperature) and SPOT VGT Normalized Difference Vegetation Index (NDVI) data were combined with land cover classification maps to analyze the change and spatial distribution of NDVI during the recent 13-year period of drought in Southwest China. A stepwise multiple regression analysis method and correlation coefficient analysis were used to examine relationships between NDVI and climate data for different land covers. The results revealed that vegetation positively responded to temperature and 70-day total precipitation during the drought period. The croplands of the in Guizhou and Guangxi provinces were seriously affected by climate factors.

Keywords: Climate factors, Correlation analysis, Drought, NDVI, Southwest China

1. INTRODUCTION

In recent years, extreme weather events and resulting severe damage have become more frequent globally. Historically, there have been rare climate anomalies (typhoons, rainstorms, floods, high temperature, drought) in some areas of China. All extreme weather phenomena have caused massive losses in industrial and agricultural production and seriously impacted the normal life of people.

Areas of Southwest China have been prone to drought every spring, but because of decreased precipitation and high temperatures from the winter of 2009 to the spring of 2010, Southwest China experienced the worst meteorological drought in 60 years. The drought has gripped large areas of the Guizhou, Yunnan, Guangxi and Sichuan provinces, and has caused more than 18 million residents and 11.7 million heads of livestock to suffer from drinking-water shortages in this Southwest region of China. Therefore, analysis of the changes potentially responsible for the drought in this region is very important.

Satellite data at global scales and resolutions that are adequate for monitoring drought conditions have now become widely available (Fensham et al., 1999; Volcani et al., 2005). There are many factors that affect meteorological drought such as temperature, precipitation, surface evaporation, soil moisture, and many studies have focused on the effects of drought and its relationship to the Normalized Difference Vegetation Index (NDVI; Guo, 2002). Time series analysis of the SPOT VGT 1-km resolution NDVI dataset has allowed scientists to examine larger scale phenomenon related to vegetation change.

Therefore, the purposes of this paper are to study changes in

NDVI and meteorological data in Southwest China over nearly 10 years and to examine the relationships between NDVI and climate data for different land covers during a period of drought per.

2. STUDY AREA AND DATA

The study region is Southwest China, which includes the Guizhou, Yunnan, Guangxi and Sichuan provinces (Figure 1A) and stretches from 20°N to 35°N latitude and from 96°E to 112°E longitude.

The land cover classification map was derived from ESA GLC (European Space Agency Global Land Cover) data, which was classified into seven types of land cover including cropland, forest, grassland, mixed vegetation, urban, bare ground, water and others (snow, no data).

Multi-temporal 10-day composite SPOT VGT NDVI data were obtained for drought periods (November to March) over 13 years from 1998 to 2010. The climate data (precipitation and temperature) were derived for 31 weather stations from the China Meteorological Data Sharing Service System (Figure 1B).

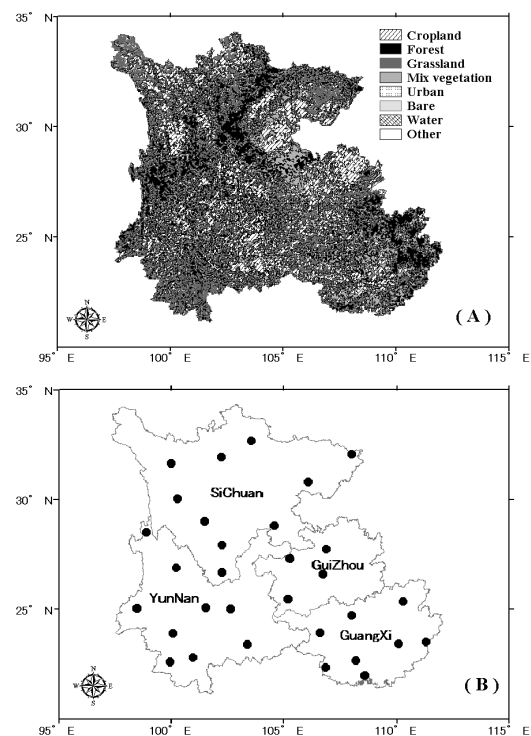


Figure 1. Land cover classification map (A) and location of weather stations (B) of Southwest China.

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3. METHOD

Historical climate data, including daily precipitation and temperature, were obtained from the China Meteorological Information Centre, for a total of 31 weather stations in Southwest China. Climate data (total precipitation and mean temperatures) were processed over 10-day periods to match 10-day composite NDVI values for each weather station. There were 36 10-day periods each year, and temperatures were averaged across the previous 10, 20, 30, 40, and 50-day temperatures. Similarly, precipitation was summed across 10, 20, 30, 40, 50, 60, and 70-day periods.

Statistical analyses included a stepwise multiple regression analysis conducted to test the relationship between NDVI and climate variables (Clark et al., 1985). To validate models derived by the linear regression analysis, adjusted R^2 s were used to adjust for the number of explanatory terms in a model. The relationships between NDVI and climate variables were also tested for precipitation and temperature considering time periods from up to 70 days earlier.

Climate values were combined into annual average data, interpolated into raster maps by the Kriging method using Surfer software, and then resampled to match the spatial resolution of the annual average NDVI data. The correlation coefficients (Gao et al., 2001) were used to analyse the relationships

between changes in NDVI and climate factors for different land covers during the period of drought from 1998 to 2010. The correlation coefficients used in this study can be formulated as follows:

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \times \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (1)$$

where x_i is the annual NDVI value, \bar{x} is mean value of NDVI in all years, y_i is the annual climatic factors (temperature or precipitation), \bar{y} is mean value of temperature or precipitation in all years; n is the number of samples; r_{xy} is correlation coefficient between NDVI and the climatic factors (temperature or precipitation).

4. RESULTS AND DISCUSSION

4.1 NDVI, Precipitation and Temperature variations

The 10-day NDVI, precipitation, and temperatures for the study region were plotted along a 13-year time series from January 1998 to March 2010. The general pattern in NDVI showed no obvious response to precipitation patterns (Figure 2). The highest NDVI's occurred in 2000, 2006, and 2009, which were also dry years. The lowest NDVI was observed in 1999

Table 1. Regression analysis results between NDVI and climate variables.

	R^2 (Adjusted)	F	Predictors / Coefficients				
All sites	0.62	97.01	MT5	SP	SP7		
			0.011	-0.003	0		
Guangxi	0.56	77.34	MT5	SP	SP7		
			0.22	-0.003	0.001		
Guizhou	0.45	30.37	MT3	T	SP7	SP	SP6
			0.008	0.013	0.002	-0.003	-0.001
Sichuan	0.46	38.82	MT4	SP	T	SP5	
			0.006	-0.005	0.007	0	
Yunnan	0.65	85.17	SP7	SP	MT5	MT3	
			0	-0.002	0.043	-0.037	

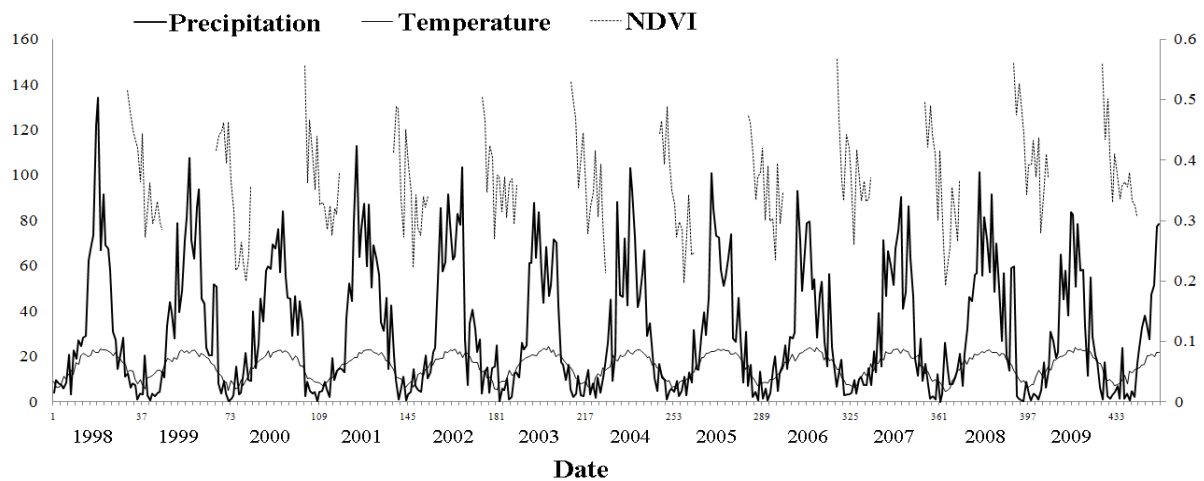


Figure 2. The patterns of NDVI (Nov. – Mar.), precipitation (mm), and temperature ($^{\circ}$ C) over 13 years (1998-2010).

following a wet year in 1998. Therefore, a simple relationship between variables for the whole region is not representative, and further evaluation is necessary.

4.2 Regression analysis

Table 1 shows the regression analysis results for NDVI and climate variables when the stepwise multivariate regression method was used, and models were used to develop all entered variables. When all weather stations were used to build the model, the mean temperature (MT5) calculated from the same period of NDVI and five previous 10-day period temperatures resulted in the highest ability to predict the NDVI variable. The next two most effective climate variables were total precipitation from the same period of NDVI (SP) and 70 day total precipitation (SP7). These three variables explained 62% of the NDVI variance. When comparing the four province areas, NDVI for the Guangxi province could be explained by MT5, SP, and SP7 (entered the model in the order) with an R^2 of 56%; NDVI for the Guizhou province could be explained by MT3, T, SP7, SP, and SP6 with an R^2 of 45%; NDVI for the Sichuan province was explained by MT4, SP, T, and SP5 with an R^2 of 46%; and NCVI for the Yunnan province could be explained by SP7, SP, MT5, and MT3 with an R^2 of 65%. Based on the coefficients of each predictor, the NDVI has a positive relationship with temperature and 70 days of total precipitation for most of the region.

4.3 Correlation between NDVI and climate variation

The annual average data (NDVI, precipitation, and temperature) for 1998 to 2010 during the drought period were used to compute the partial correlation coefficients at the pixel scale for Southwest China. Statistically significant tests were based on the t-test ($P < 0.05$). According to the correlation coefficients values, we generated the correlation degree into four classes: negative (below 0), weak (0–0.53), moderate (0.53–0.75) and strong (above 0.75).

Figure 3A is a map of the correlation degree between annual average NDVI and precipitation. When the statistically significant level is 0.05, the partial correlation coefficients must be greater than 0.5324. It shows that moderate and strong correlations between the NDVI and precipitation were mainly in the Guizhou and Guangxi provinces but, for most of the Sichuan area, the statistical relationship between NDVI and precipitation was not significant.

Figure 3B is a map of the correlation degree between the annual average NDVI's and temperatures. The dark gray and black areas are the ones where the partial correlation coefficients between NDVI and temperature are bigger than 0.5324 ($P < 0.05$). The significant areas are distributed across the Sichuan and Guizhou provinces, but not the Yunnan province.

To better analyse the correlations among the three factors in this region, land cover classifications were assessed. Table 2 presents the interactions between NDVI and climate factors for the differences in land cover types from 1998 to 2010. The results show that all of the correlation coefficients for the relationship between NDVI and temperature for each land cover type were positive, especially in the Guizhou province (0.52–0.57). The correlation coefficients for the relationships between NDVI and precipitation in cropland of the Guangxi and Guizhou provinces are both 0.04, but the correlation coefficients are negative for other types of land cover. Therefore, we can see that precipitation and temperature significantly affect agriculture in the Guizhou and Guangxi

Table 2. The correlation coefficients in different land cover types

	Land cover	Area (%)	R (NDVI - preci.)	R (NDVI - temp.)
Guangxi	Crop	4.48	0.04	0.35
	Forest	5.58	-0.15	0.35
	Grass	1.93	-0.02	0.35
	Mix	5.62	-0.04	0.34
Guizhou	Crop	5.81	0.04	0.54
	Forest	2.20	-0.09	0.52
	Grass	2.20	-0.06	0.54
Sichuan	Mix	3.63	-0.01	0.57
	Crop	13.02	-0.21	0.40
	Forest	11.14	-0.31	0.43
Yunnan	Grass	6.92	-0.19	0.33
	Mix	6.76	-0.18	0.45
	Crop	9.16	-0.08	0.23
	Forest	8.97	-0.17	0.29
	Grass	4.82	-0.07	0.18
	Mix	6.17	-0.08	0.26

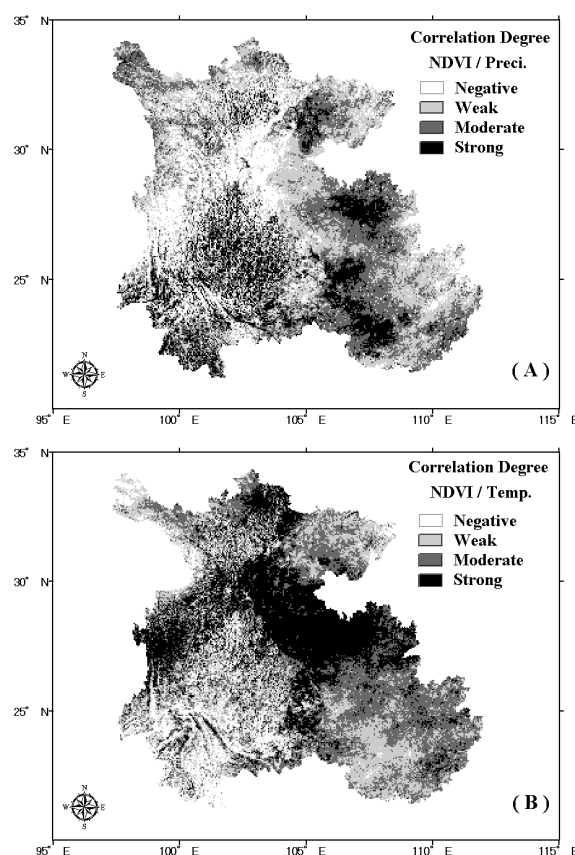


Figure 3. Map of correlation degree between NDVI and precipitation (A). Map of correlation degree between NDVI and temperature (B).

provinces. It is also consistent with the severe drought in these two areas reported by 2010 news.

5. CONCLUSION

Our study showed that NDVI, precipitation, and temperature varied among years. The correlation between NDVI and temperature was significantly higher than between NDVI and precipitation during the drought period (November to March). Based on regression analysis, the results showed that the NDVI was related to temperature and 70-day total precipitation. From the correlation degree map, we can see the pattern change of the correlation between NDVI and climate factors. Combined with land cover classification, the results show that in Guizhou and Guangxi provinces, NDVI was more seriously affected by climatic factors (precipitation and temperature), especially for agricultural areas from 1998 to 2010. In the future, research may incorporate agricultural production and surface evaporation data to further evaluate the mechanisms by which these factors interact during periods of drought.

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