Int. J. Environ. Res., 5(1):139-148, Winter 2011
ISSN: 1735-6865

Drought Risk Assessment in Western Inner-Mongolia

Lin, M. L.[1] Chu, Ch. M.[2*] and Tsai, B. W.[2]

[1] Department of Tourism, Aletheia University, 32, Zhenli St., Danshui Town, Taipei County 25103, Taiwan

[2] Department of Geography, National Taiwan University, No. 1 Sec. 4 Roosevelt Road, Taipei 10617, Taiwan

Received 12 Sep. 2009; Revised 17 Aug. 2010; Accepted 25 Aug. 2010

ABSTRACT: The objective of this study is to develop a novel methodology integrating remote sensing, geographic information system technology and local spatial autocorrelation geo-computation for quick drought assessment. One group of drought indices, based on the condition of the vegetation, includes the Normalized Difference Vegetation Index (NDVI), Anomaly of Normalized Difference Vegetation Index (NDVIA) and Standardized Vegetation Index (SVI). The other group, based on the moisture conditions, includes the Normalized Difference Moisture Index (NDMI) and Standardized Moisture Index (SMI). The local G-statistic (G_i^*) provides insight into the spatial relationships of the drought indices for drought risk assessment. Specifically, locations with significant Gi* values indicate spatial clusters where there are differences between the vegetative and hydrological drought indices. The results of spatial co-occurrence analysis indicate the existence of hot spots where the drought indices are spatially stable. This spatial information can be used to identify high drought risk areas as a first step towards helping local administrators improve the allocation of local water resources in arid environments. Finally, the novel methodology, integrating remote sensing, geo-computation and geographic information techniques, is demonstrated. The results indicate its effectiveness for quick drought assessment.

Key words: NDVI, NDMI, Remote sensing, Local G-statistic

INTRODUCTION

Drought is a major environmental problem in arid and semi-arid environments. However, the drought phenomena show high variability in time and space making it very difficult to exactly identify the spatial location of such areas. GIS-based spatial analysis has been widely used in environmental studies during recent years (Shobeiri *et al.*, 2007; *Pijanowski et al.*, 2009; Solaimani *et al.*, 2005; Rowshan *et al.*, 2007; Mahiny and Gholamalifard, 2007; Alam *et al.*, 2008; Joarder *et al.*, 2008; Faryadi and Taheri, 2009). Remote sensing methods have already been applied to monitor vegetation changes in a number of regions worldwide (Al-Bakri and Taylor, 2003; Anyamba and Tucker, 2005; Karlsen *et al.*, 2008; Neigh *et al.*, 2008; Lin and Chen, 2010). For example, satellite images and geo-statistical methods have been used to assess land degradation and land cover change in the Central Asian deserts (Karnieli *et al.*, 2008).

In recent years satellite images have been widely utilized as a tool for monitoring and assessing drought conditions (Bhuiyan *et al.*, 2006; Martyniak *et al.*, 2007; Bajgiran *et al.*, 2008; Lin *et al.*, 2009). For example, a time-series of AVHRR vegetation indices taken during the period from 1981-2003 has been used to assess seasonal and inter-annual vegetation dynamics in Argentina (Seiler *et al.*, 2007). Analytical results have shown that vegetation indices are useful for identifying environmental variations and the impact of climatic anomalies on vegetation and crop production. Bajgiran *et al.* (2008) found a significant correlation between normalized difference vegetation index (NDVI) values and precipitation data obtained from meteorological stations. They used NDVI values for the monitoring and mapping of regional drought conditions in Northwestern Iran. Satellite data has also been utilized to monitor vegetation cover, to detect the effects of drought in Mongolia (Tachiiri *et al.*, 2008).

Recent studies suggest that there is a high correlation between the Normalized Difference Moisture Index (NDMI) and wetness (Jin and Sader, 2005). Gao first proposed the Normalized Difference Water Index

*Corresponding author E-mail: d91228003@ntu.edu.tw

(NDWI) in 1996, demonstrating that it can show changes in the liquid water content of vegetation canopies (Gao, 1996). The NDMI is based on the contrast between mid infrared (MIR) and near infrared (NIR) reflectance making it sensitive to changes in vegetation leaf structure and water content (Hayes and Cohen, 2007; Goodwin *et al.*, 2008; Hayes *et al.*, 2008). The index has also proven to be a useful technique for monitoring harvesting and other disturbances in the monitored area (Wilson and Sader, 2002). The NDMI has been demonstrated to be an improvement over the NDVI for the detection of changes in forest cover (Hayes and Cohen, 2007). Many studies have shown that the state of local vegetation and soil moisture content can be monitored and assessed effectively using remote sensing techniques.

This study proposes a novel methodology for drought risk assessment and for mapping the high drought risk area. The integration of remote sensing, geo-computation and geographic information techniques helps overcome the problem of lack of ground truth data to provide a method for quick spatial drought assessment. This methodology forms the basis for estimating the spatial extent of the area of high drought risk, thus making possible assessment of various drought management alternatives. We also conduct a case study, distinguishing between images presenting dry and wet conditions to provide a visual geographic comparison of high drought risk area. To the best of our knowledge, this is the first geo-computation method using satellite derived drought indices to be specifically applied for drought risk assessment with a focus on an oasis ecosystem in an arid environment.

MATERIALS & METHODS

In this study we use the bi-weekly MODIS Vegetation Indices (16-Day L3 Global 250m product) for the period from June 2001 to August 2006 (2001-2006 is used as the base period). The NDVI is a useful measure for monitoring vegetation dynamics. The NDMI is compiled by combining MIR spectral information correlated to moisture content (Jin and Sader, 2005; Hayes and Cohen, 2007). The values of the NDVI and NDMI vary in response to environmental factors such as drought conditions. The NDVI derived vegetative drought indices and the NDMI derived hydrological drought index, which is related to land surface moisture content, both provide important information for drought risk assessment.

Oases are of great ecological importance in the arid environments. An effective approach is needed for quickly identifying high drought risk areas from remotely sensed images of arid environments. We propose using anomalies in the normalized difference vegetation index (NDVIA), standardized vegetation index (SVI), and standardized moisture index (SMI) to evaluate the degree of drought risk. The NDVIA indicates drought conditions by showing the departure from the long-term average for a specific month in comparison to the average range (Anyamba *et al.*, 2001; Bayarjargal *et al.*, 2006). Gutman *et al.* (1996) proposed a land monitoring technique based on the finding of standardized anomalies. Liu and Juárez (2001) suggested the use of standardized anomaly data instead of mean values to be more suitable for investigating the annual departure of the NDVI from the normal. Peters et al. (2002) suggested the integration of the Standardized Vegetation Index (SVI) as one factor when assessing climatic and anthropogenic impacts. The SVI can be used to describe the deviation of vegetation from the normal state (Gutman *et al.*, 1996; Liu and Juárez, 2001; Peters *et al.*, 2002). In this study, we propose a standard moisture index (SMI), similar in form to the SVI, to evaluate land surface moisture conditions. The standardized anomaly SMI is computed by subtracting the sample mean of the NDMI, then dividing by the corresponding sample standard deviation of the NDMI. The NDVIA and SVI can be applied to identify vegetative drought conditions and relative vegetative drought risk. The SMI was applied to identify hydrological drought conditions and relative hydrological drought risk. Ecologists enrich their understanding of spatial processes occurring in the ecosystem by studying spatial structures (Legendre, 1993). The Getis-Ord's G_i^* statistic (local G-statistic) method has been applied in a variety of studies to identify spatial clusters of a given phenomena (Getis and Ord, 1992; LeDrew *et al.*, 2004; Lin, 2004; Lees, 2006; Wulder *et al.*, 2007; Tsai *et al.*, 2009). Here, spatial autocorrelation analysis is used to identify those spatial clusters with statistical significance for high drought risk. The local Getis statistic is used to measure spatial autocorrelation at the local level from which it generates clusters of hot (cold) spots indicating spatial distributions of the given phenomena. The value of G_i^* is calculated at the cut-off distance d, which is defined as the smallest distance which ensures that each sample point has at least one neighbor. We found that a separation distance of 500m ensured that all samples had at least one neighbor. The local G-statistic is calculated for each pixel in the satellite image using the equation from Tsai *et al.* (2009). Assuming that $Gi^*(d)$ is approximately normally distributed (Getis and Ord, 1992), the output from $Gi^*(d)$ can be interpreted as a standard normal variant with an associated probability from the z-score distribution. A high Gi^* value indicates that high values are clustered near each other. Thus, only positively significant clusters (with 95, 99 and 99.5 percent significance levels from a two-tailed normal distribution) are mapped to provide geographic information of high drought risk. In a case study the local Getis statistic is computed for NDVIA, SVI and SMI data to examine the relative drought risk and characteristics of the Ejina oasis. The study area was located in the Ejina basin, in Inner-Mongolia, western China (Fig. 1) (latitude N 40° 30' - N 42° 30' and longitude E 99° 03' - E 100° 00'), covering an area of about 845 km^2. It has a semi-arid climate, dry for most of the year except for the summer season. The mean annual precipitation in this region is 40.3 mm. The mean annual evaporation is between 3700 to 4000 mm, with a maximum of 4756 mm (Xue *et al.*, 2006). The vegetation consists mainly of grasslands and Populus euphratica forests. The variation in the water supply in the basin creates seasonal variation in growth of vegetation. Seasonal runoff from nearby mountains (with elevations higher than 2000m) also has a big influence on land cover variability in the Ejina basin.

Over the past decade, regional climate change and human activities in western China have led to serious land degradation, especially in the oases (Liu and Li, 2004; Su *et al.*, 2004). Zhang *et al.* used Thematic Mapper (TM) imagery to detect land cover changes. They found that the riparian woods in the Ejina Oasis region had decreased by 45% in the period from 1982 to 2000 (Zang *et al.*, 2005). Their results also showed that the area covered by water had decreased dramatically by 93% over the same period of time. In another study NOAA/AVHRR satellite data were used to monitor variation in the Eijin Oasis area during the period from 1991 to 2001 (Xue *et al.*, 2006). They found a clear decline in the area covered by vegetation.

The spatial extent of Ejina Oasis is difficult to delineate exactly because the green areas expand from spring to fall and decrease from fall to spring (Lin and Chen, 2010). Summer is the critical growing season when vegetation activity is at its maximum. Thus, we selected summer satellite images from the year 2003 and 2004 as examples to demonstrate the effectiveness of the local G-statistic and spatial co-occurrence analysis to identify spatial information in drought risk areas. The summer of the year 2003 represents the dry conditions and the summer of the year 2004 represents the wet conditions (Lin and Chen, 2010).

RESULTS & DISCUSSION

Fig. 2 shows MODIS images indicating summer vegetation conditions for the years 2003 and 2004. The 2003 and 2004 images depict relatively drier and wetter vegetation conditions. The summer NDVI values for

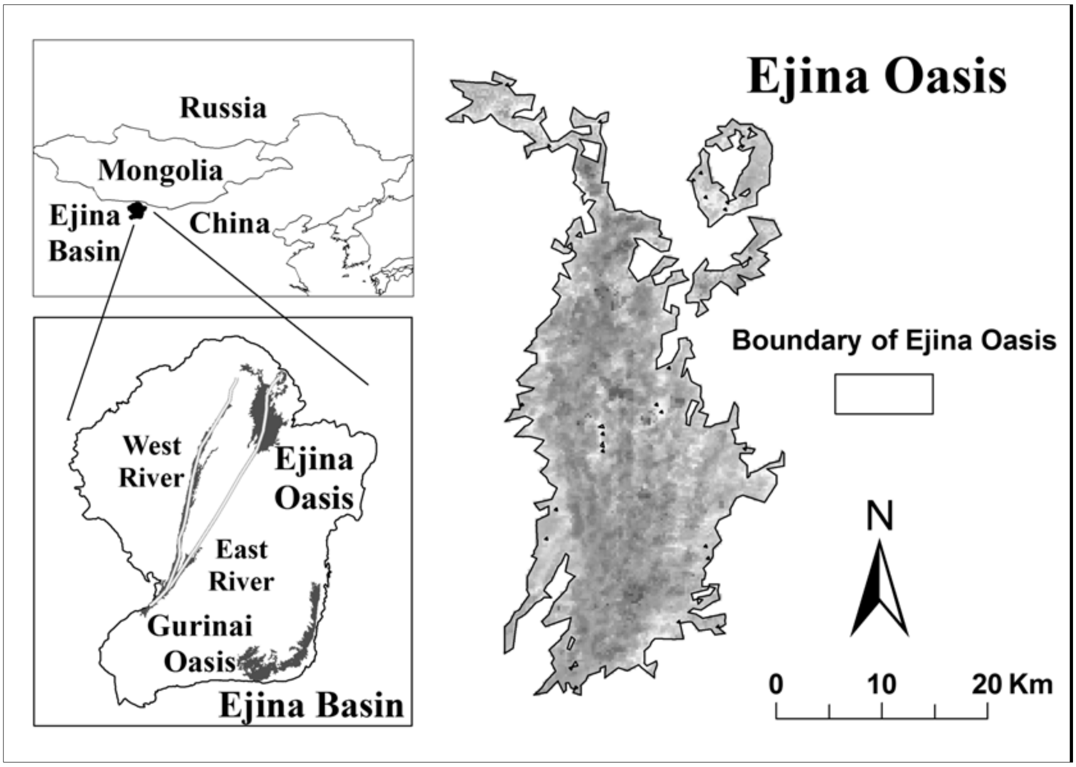

Fig. 1. Location of the Ejina basin and study area (Ejina Oasis)

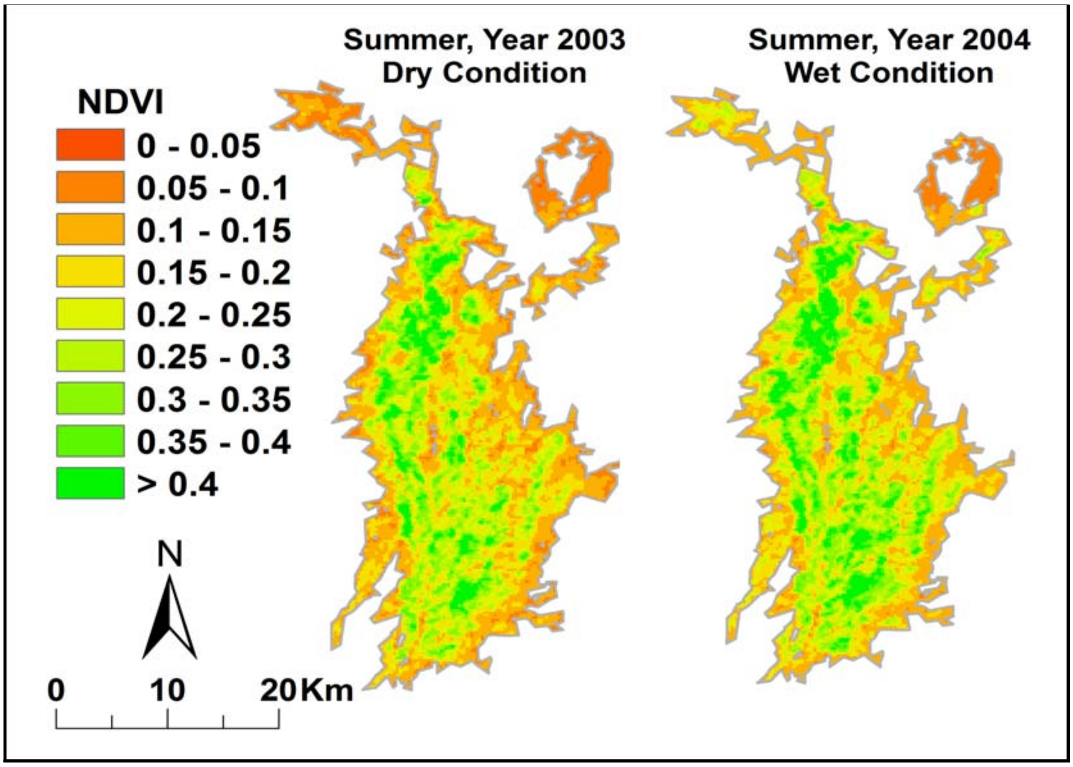

Fig. 2. Spatial distribution of NDVI in the Ejina Oasis during summer of 2003 and 2004

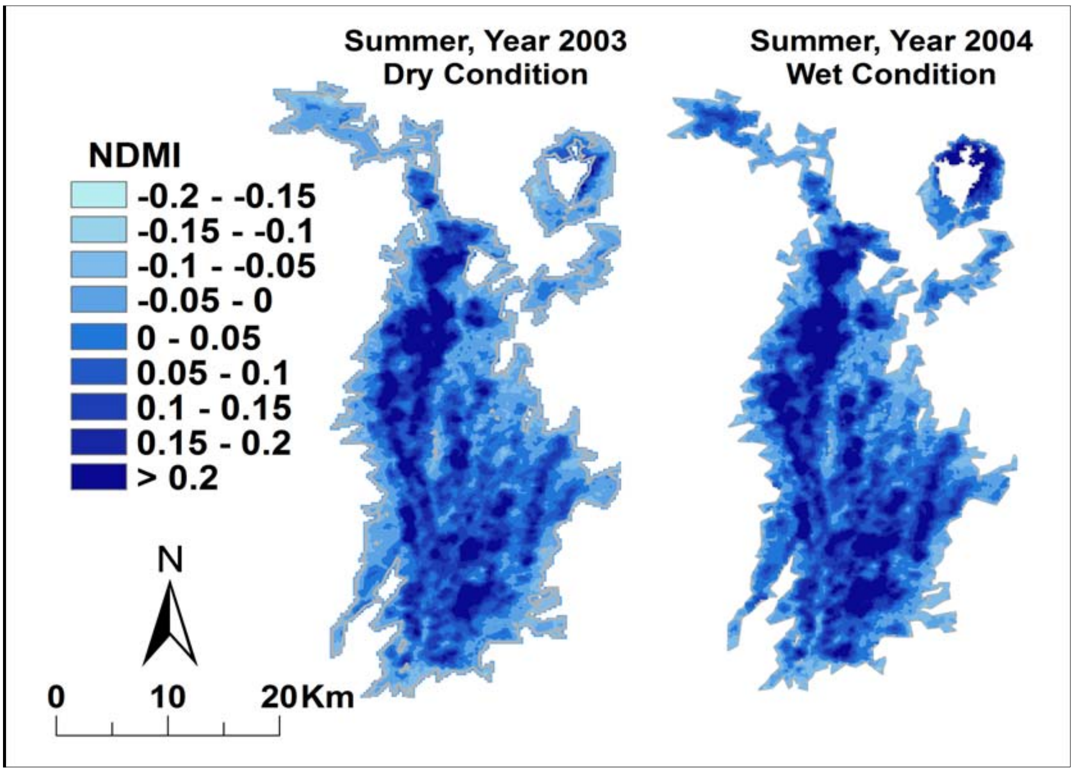

Fig. 3. Spatial distribution of NDMI in the Ejina Oasis during summer of 2003 and 2004

year 2003 ranged from 0.04 to 0.59 and the summer NDVI values for year 2004 ranged from 0.04 to 0.62. Fig. 3 gives a general illustration of the NDMI distri bution, suggestive of land surface moisture conditions in the Ejina Oasis in the summer of the years 2003 and 2004. The summer NDMI values for the year 2003 ranged from -0.17 to 0.44 and the summer NDVI values for the year 2004 ranged from -0.13 to 0.48. A comparison of the NDVI and NDMI images indicates that 2003 was relatively drier than 2004.

The local G-statistic helps detect significantly different areas, termed spatial clusters, for high drought risk area. Figs. 4, 5 and 6 show the significant G_i^* values (£\=0.05, 0.01, and 0.005) for the NDVIA, SVI, and SMI. The areas of high drought risk identified by NDVIA are 284 km^2 and 152 km^2 for the years 2003 and 2004, respectively. The areas of high drought risk identified by SVI are 271 km^2 and 190 km^2 for the years 2003 and 2004, respectively. The areas of high drought risk identified by SMI are 309 km^2 and 194 km^2 for the years 2003 and 2004, respectively. The results demonstrate the usefulness of the satellite derived drought indices applied for drought risk assessment in cases when ground truth data is lacking.

Also visible in Figs. 4, 5 and 6 are the intensification of the high drought risk in 2003 in the Ejina Oasis. The spatial patterns indicated by the local G-statistic are similar for the different drought indices. The analytical results demonstrate the stability and usefulness of satellite derived drought indices for quick drought assessment.

The local G-statistic results help to identify spatially homogeneous areas of relatively high drought risk. The extent and distribution of the spatial clusters throughout the oasis seem reasonable, given the spatial pattern of high drought risk. The spatial clusters can be viewed as geographic measures for monitoring drought anomalies or detecting areas of high drought risk. Overall, the local G-statistic images show the areas having the most significant drought anomalies (which would be high drought risk areas). This spatial information is important. It can be used to guide the local administration to prioritize water resources when serious drought occurs. Therefore, the local G-statistic should be part of knowledge-discovery approaches for large scale drought monitoring and assessment.

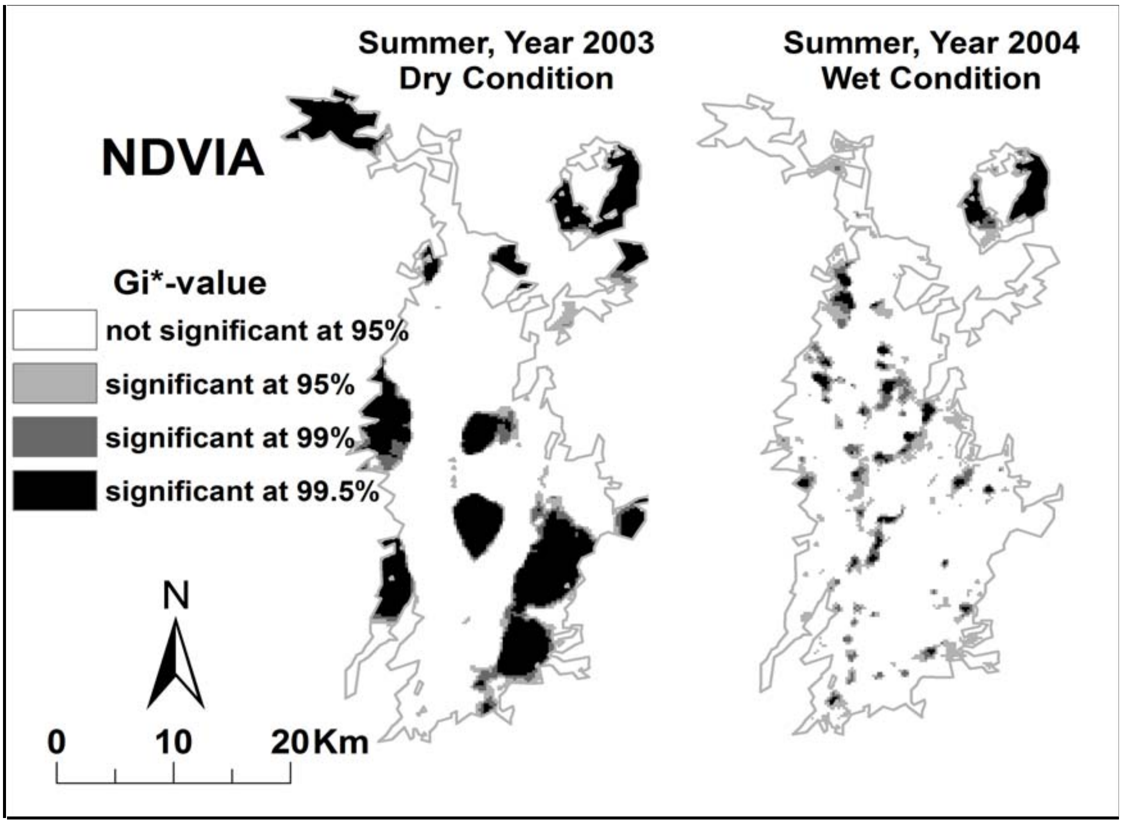

Fig. 4. An data classification based on significance thresholds (95, 99, and 99.5%) is used to present spatial clusters for NDVIA

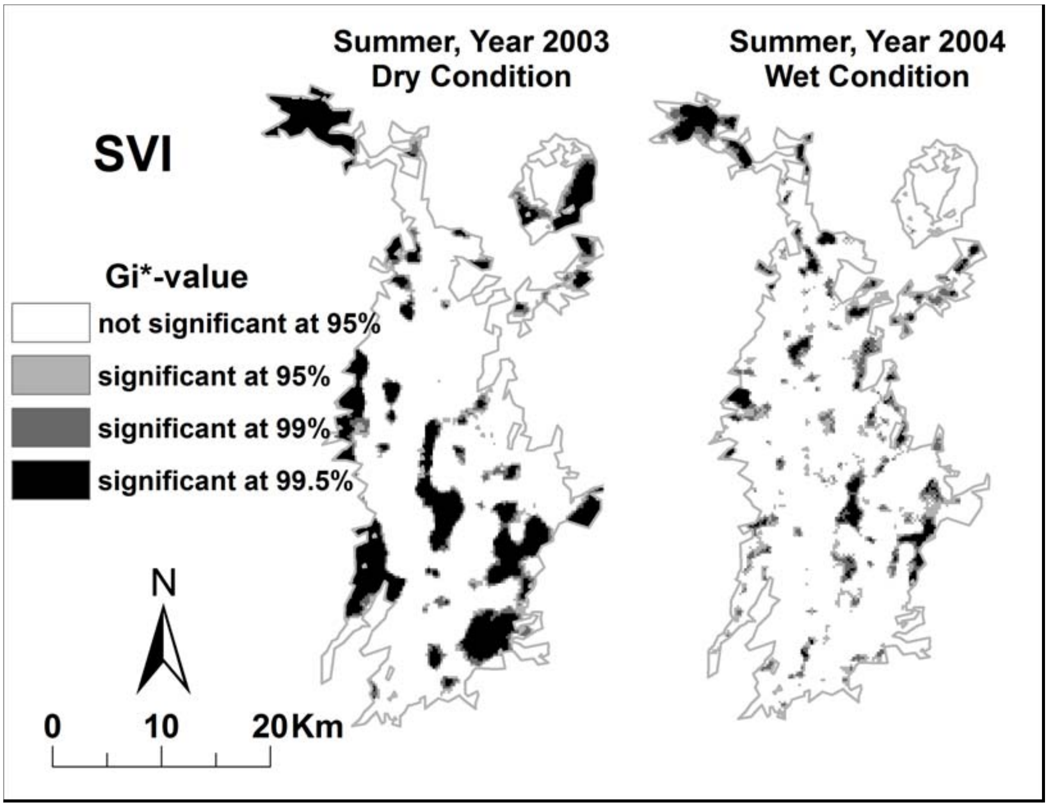

Fig. 5. An data classification based on significance thresholds (95, 99, and 99.5%) is used to present spatial clusters for SVI

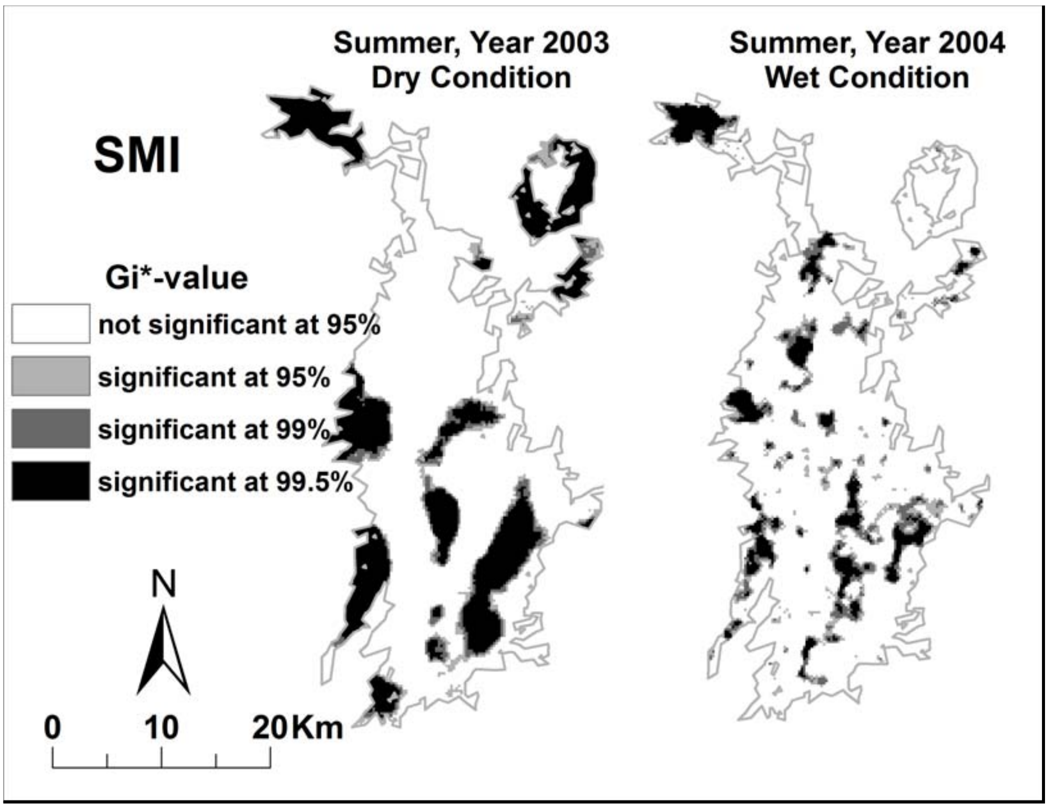

Fig. 6. An data classification based on significance thresholds (95, 99, and 99.5%) is used to present spatial clusters for SMI

The use of the local G-statistic method is not only advantageous for identifying spatial clusters of high drought risk areas, but also provides a visual basis for spatial comparison between drought indices. A geographical comparison of the maps in Figs. 4 , 5 and 6 shows the overlaying of high-value cells for drought indices. Although Figs. 4, 5 and 6 show some general spatial clusters between the different drought indices, the spatial distribution of these clusters is heterogeneous, with many isolated patches and single pixels. Thus, a spatial co-occurrence analysis (geographical overlay GIS analysis) is carried out to count the times the drought indices occur in the same cell. A map showing this new geographical information is shown in Fig.7.

In general, the light gray, mid-gray and black clusters indicate the exact spatial extent and clustering of areas of high drought risk, based on the co-location pattern of drought indices. The spatial distribution of the clusters appears to fit the phenomenon of vegetation/drought conditions in the study area. These clusters can be viewed as geographical hot spots of relatively high drought risk. It must be emphasized that these are only areas with potential for high drought risk. The result of spatial co-occurrence analysis is helpful for quick large scale geographical investigation of the potential/relative high drought risk. The Ejina Oasis study area is a good example for demonstrating the importance of the cluster concept (using local the G-statistic) for drought monitoring and spatial assessment. As mentioned earlier, integration of the drought indices, local G-statistic geo-computation and spatial co-occurrence analysis is only the first step in identifying high drought risk areas. These analysis results should be indentified and confirmed by field investigations. In brief, the phenomenon of clustering of drought indices provides an alternative viewpoint for drought monitoring and assessment, especially in drought risk assessment.

CONCLUSION

This study is successful in delineating detailed spatial information of high drought risk areas from MODIS imagery taken in the summer months of the years 2003 and 2004. There is good spatial agreement

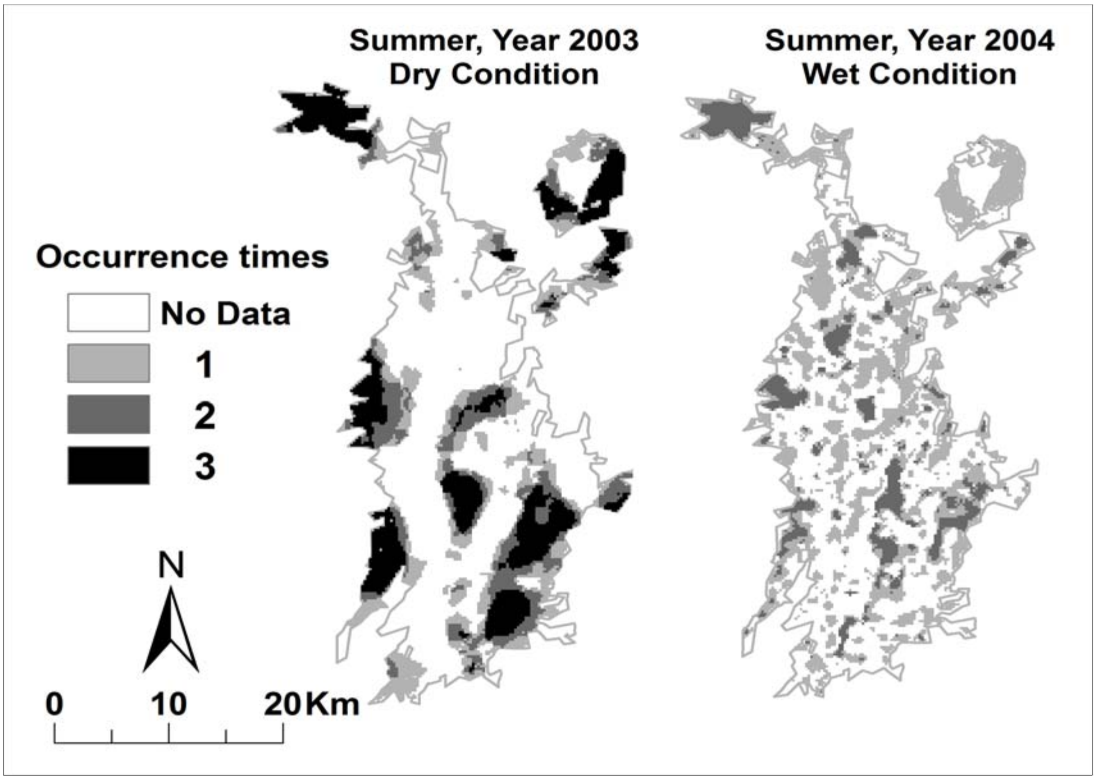

Fig. 7. Delineation of spatial clusters showing high drought risk areas where 1 indicates the area identified by one of the drought indices (NDVIA, SVI, and SMI); 2 indicates the area identified by two of the drought indices; 3 indicates the area identified by all drought indices

between the different satellite-derived drought indices (NDVIA, SVI and SMI). The results demonstrate that the indices allow spatial identification of the areas at risk of drought and should be of significant help for drought assessment. The local G-statistic emphasizes the patterns of drought risk and data characteristics inherent in spatial data derived from remotely sensed imagery.

The results demonstrate the effectiveness of integrating remote sensing, geo-computation and geographic information techniques for quick drought assessment on the large scale when ground truth data is lacking. The spatial extent of high drought risk areas can be effectively monitored and assessed using satellite data and these spatial statistics. The method can be improved to play an important role, leading to more integrated analysis and obtaining a holistic view of arid and semi-arid environments. This is an alternative way of viewing and evaluating vegetation and drought conditions, mainly through drought indices, local G-statistics and spatial co-occurrence analysis.

This information is needed by government decision makers to identify the degree of drought stress for the oases as an integrated ecosystem. Practitioners and decision makers can get a better spatial insight of regional drought conditions and arrange water resources accordingly. Moreover, we suggest that this novel methodology should be applied in arid environments to enrich both theoretical and practical development of spatial/ecological monitoring and assessment.

ACKNOWLEDGEMENTS

The authors would like to thank the National Science Council of the Republic of China, Taiwan, for their financial support of this research under contract nos. NSC98-2410-H-156-015, NSC96-2415-H-156-003-MY2 and NSC95-2415-H-156-007. The authors are also most grateful for the kind assistance of Prof. Abdoli, M. A., Editor-in-Chief of the International Journal of Environmental Research, and for the constructive suggestions of the anonymous reviewers, all of which has led to the making of several corrections and suggestions that have greatly aided us in improving the presentation of this paper.

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