AGRICULTURAL DROUGHT RISK ASSESSMENT USING REMOTE SENSING AND GEOGRAPHIC INFORMATION SYSTEM

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ABSTRACT: The 4 sets of environmental variables dealing with meteorology, hydrology and physiography were analyzed to generate a spatial drought risk index of Phitsanulok province of Thailand. The analysis of K-mean and discriminant were applied to the set of the selective drought variables for grouping each of spatial variable set into 4 classes. The obtained 4 classes, based on group statistics, were thus recoded in the meaning of no risk, low risk, moderate risk, and high risk. The regression coefficient between recoded classes and a set of the selective environmental variables were then applied as spatial variable weighting on thematic dataset in GIS spatial analysis. The results showed that the weighting score of drought variable was highest in meteorological variable compared to other variables.
KEYWORDS: Agricultural Drought Risk, Spatial Analysis

1. Introduction

In the nature of drought, rainfall is a crucial factor because it acts as a source of water in soil and in reservoirs. Normally, the meteorological drought is based on precipitation's departure from a normal range over some period of time. When precipitation is reduced or deficient for a period, the hydrological drought is subsequently occurred. The agricultural drought occurs when there is not enough soil water or supplied water to meet the demand of a particular crop. According to global climatic change, an evaluation of drought risk area is focused on agricultural regions. The agricultural drought in developing countries can much impact on economy, society, and environment. Geographic information system (GIS) has been used as an effective tool for evaluating spatial drought risk. A GIS based drought risk is typically a result of a set of spatial environmental factors with respect to meteorological, hydrological, and physiological characteristics of a specified area. These three factors include many variables and generally analyzed by using a linear combination weighting system or criteria assessment method. By using such method, however, a modification of either scoring or weighting of some drought variables was required to fulfill spatial variation of available data.

This objective of this study was to determine agricultural drought risk index which was based on a statistical weighting model of spatial environmental variables. The 15 spatial variables, which are typically the causes of spatial drought risk, were analyzed for determining a drought risk index for Phitsanulok province. This province covers the area about 10,815 Km^2. The study area locates in the lower northern part of the Thailand with geographical extent from 590500E to 725500E and from 1963500N to 1804000N.

2. Methodology

The spatial drought risk index was developed from the 15 environmental variables which were divided into 4 sets: (1) annual rainfall (RF), annual rain day (RD), and daily maximum rainfall (RM), statistically recorded during 1995-2002 from the local meteorological stations, (2) density of man-made well (WE), groundwater yield of aquifer (AQ), available groundwater (GW), density of stream network within a sub-watershed (WS), size of sub-watershed (WZ), (3) distance from perennial stream network (ST), distance from surface water bodies (WB), distance from pumping irrigated station (PU), and distance from irrigation area (IR), and (4) soil drainage (SO), slope (SL), and elevation (EL). The thematic methodologies for deriving the statistical weighting model of spatial environmental variables are displayed in Fig 1. The agricultural drought risk index, thus, was verified by vegetation index (NDVI), vegetation temperature index (VT), and evapotranspiration (ET), which were developed from MODIS data, acquired in 2002 on January 31, February 16, March 13, and March 29. The indices of VT and ET for area in Thailand were computed from the AVT and ET models, proposed by Chada (Chada, 2002 and 2002).

3. Results

The GIS-based drought risk models were formed from the regression coefficients between discriminant classes and the standardized values. The models are expressed as follows:

$$DI_M\ (R = 0.90) = (-0.520*[RF]) + (-0.313*[RD]) + (-0.219*[RM]) \tag{1}$$

$$DI_{H1}(R= 0.93) = (-0.197*[WE]) + (-0.166*[AQ]) + (-0.556*[GW]) + (-0.047*[WS]) + (0.474*[WZ]) \tag{2}$$

$$DI_{H2}\ (R= 0.93) = (-0.005*[ST]) + (0.178*[WB]) + (0.038*[PU]) + (0.908*[IR]) \tag{3}$$

$$DI_P\ (R = 0.90) = (0.529*[SO]) + (0.359*[SL]) + (0.287*[EL]) \tag{4}$$

$$DI_O\ (R = 0.94) = (0.373*[DI_M]) + (0.343*[DI_{H1}]) + (0.308*[DI_{H2}]) + (0.321*[DI_P]) \tag{5}$$

The overall drought model (DI_O) showed that the drought risk index was most respectively depended on DI_M, DI_{H1}, DI_P, and DI_{H2}. The maps of drought risk indices produced from the above equations are shown in Figure 1 and 2. The means of the 15 variables of each 4 class and the correlation between DI_O and 15 variables are shown in Table 1.

In order to explore relations in the hot seasonal VT, ET, NDVI and DIo, the correlation coefficients were performed (Table 2). The DIo showed negative correlation with VI and VT while it showed positive correlation with ET. From this Table, it can be concluded that the DIo developed in this study was reliable when it was considered by using MODIS-derived indices, such as VT, ET, and NDVI. During hot season (January-April), where the DIo indicated no risk and low risk, the growing crop can be observed in the MODIS-NDVI and MODIS-VT. Fig. 2 is showed the visual agreements between map of DIo and RGB images of MODIS indices, acquired in hot season.

4. Conclusions

To derive scoring or weighting of some drought variables in GIS spatial analysis, the weighting of spatial environmental variables using statistically approaches, K-mean clustering and discriminant analysis, and regression, was practical. The agricultural drought risk index determined obtained from the method used in this study was reliable when it was considered by using MODIS-derived indices, such as VT, ET, and NDVI.

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References

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Table 1. Correlation (R) between DIo and Environmental Variables and Means of Environmental Variables in Drought Risk Index (SO*: poorest drainage = 1, poor drainage = 2, moderate drainage = 3, and well drainage = 4)

Variable	R	unit	DI_O			
			No	Low	Mod	High
RF	-0.59	mm.	1246.00	1284.56	1249.32	947.88
RD	-0.54	day	88.12	83.88	81.25	59.12
RM	-0.77	mm.	229.50	182.95	149.60	66.58
ST	0.31	Km	1.44	1.61	1.82	2.66
WB	0.26	Km	3.47	3.64	3.87	4.00
PU	0.05	Km	3.19	2.69	3.15	3.04
IR	0.51	Km	2.22	3.59	4.00	4.00
WE	-0.34	skm	19.71	7.64	4.01	1.66
AQ	-0.53	m^3/h	12.98	12.19	9.26	7.52
GW	-0.51	m^3/h.	13.61	11.29	8.33	5.47
WS	-0.48	Km/Km^2	0.32	0.30	0.22	0.09
WZ	0.51	Km^2	1154.19	2387.50	6239.20	11292.61
SO*	0.53	*	2.02	2.18	2.75	3.44
SL	0.65	%	0.13	0.63	3.08	11.89
EL	0.52	m.	60.39	81.68	145.66	276.46

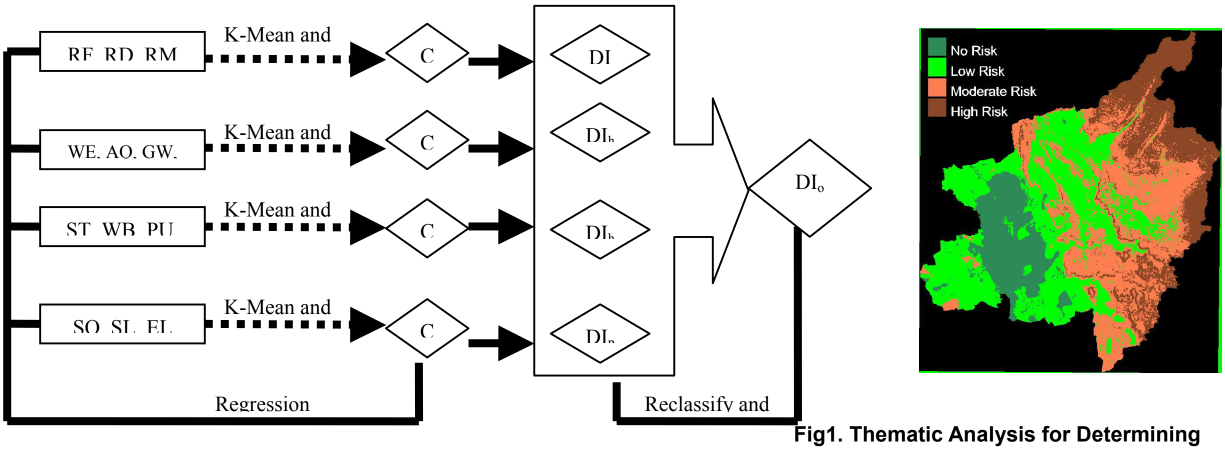

Fig1. Thematic Analysis for Determining Drought Risk Indices

Table 2. Correlation between MODIS Indices and DIO (The Acquired Dates of MODIS Data were January 31 (“0131”), February 16 (“0216”), March 13 (“0313”), and March 29 (“0329”))

	VT$_{0131}$	VT$_{0216}$	VT$_{0313}$	VT$_{0329}$	ET$_{0131}$	ET$_{0216}$	ET$_{0313}$	ET$_{0329}$	VI$_{0131}$	VI$_{0216}$	VI$_{0313}$	VI$_{0329}$	DI$_{O}$
VT$_{0131}$	1	0.73	0.45	0.09	-0.26	-0.29	-0.34	-0.32	0.91	0.78	0.47	-0.04	-0.13
VT$_{0216}$	0.73	1	0.80	0.43	-0.15	-0.63	-0.66	-0.68	0.69	0.96	0.78	0.21	-0.48
VT$_{0313}$	0.45	0.80	1	0.72	-0.19	-0.70	-0.76	-0.79	0.39	0.70	0.98	0.51	-0.59
VT$_{0329}$	0.09	0.43	0.72	1	-0.14	-0.56	-0.70	-0.67	0.05	0.30	0.64	0.92	-0.54
ET$_{013}$	-0.26	-0.15	-0.19	-0.14	1	0.12	0.21	0.15	0.16	-0.14	-0.17	-0.08	0.20
ET$_{0216}$	-0.29	-0.63	-0.70	-0.56	0.12	1	0.71	0.76	-0.25	-0.38	-0.63	-0.33	0.58
ET$_{0313}$	-0.34	-0.66	-0.76	-0.70	0.21	0.71	1	0.86	-0.27	-0.53	-0.62	-0.46	0.58
ET$_{0329}$	-0.32	-0.68	-0.79	-0.67	0.15	0.76	0.86	1	-0.28	-0.53	-0.69	-0.33	0.70
VI$_{0131}$	0.91	0.69	0.39	0.05	0.16	-0.25	-0.27	-0.28	1	0.73	0.41	-0.06	-0.05
VI$_{0216}$	0.78	0.96	0.70	0.30	-0.14	-0.38	-0.53	-0.53	0.73	1	0.70	0.14	-0.35
VI$_{0313}$	0.47	0.78	0.98	0.64	-0.17	-0.63	-0.62	-0.69	0.41	0.70	1	0.46	-0.54
VI$_{0329}$	-0.04	0.21	0.51	0.92	-0.08	-0.33	-0.46	-0.33	-0.06	0.14	0.46	1	-0.32
DI$_{O}$	-0.13	-0.48	-0.59	-0.54	0.20	0.58	0.58	0.70	-0.05	-0.35	-0.54	-0.32	1

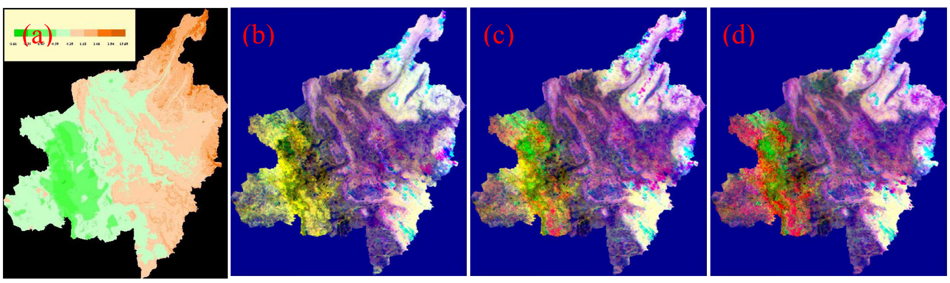

Figure 2. Map of DIo (a), and RGB Images of VI0131, VI0216, DIo (b) VI0131, VI0313, DIo (c) VI0131, VI0329, DIo (d)