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Estimation of KBDI (Drought Index) in Real-Time Using GIS and Remote Sensing Technologies

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Abstract. *Forest fire managers across United States use drought indices for assessing wildfire risk. KBDI is a widely used drought/fire index that indicates the amount of moisture deficiency in the deep duff and upper soil layers. Current practice of computing KBDI from point source weather data and its manual interpolation across counties are subject to uncertainties. A real-time system has been developed for computing KBDI from remotely sensed data and GIS. Air temperature and precipitation data needed for computing KBDI are derived from AVHRR satellite and NEXRAD radar respectively. Use of GIS and remote sensing technologies overcomes the uncertainties involved in the computation of KBDI. The spatial resolution of the data has also been improved with the use of remotely sensed data and GIS from county level to 1km × 1km.*

Keywords. KBDI, AVHRR, NEXRAD, Wildfire, real-time, Drought Index.

Introduction

Every year thousands of hectares of grassland and forests are lost due to wildfires. These fires cost millions of dollars in economic loss and cause irreparable damage to the environment. According to United States Forest Service year 2000 was the most challenging year in record with over 6.5 million acres scorched by fire. The reason for this huge loss of forested land to fire is due to severe drought during the year 2000. Forest fire managers across United States use fire potential indices or drought indices for assessing wildfire risks and for alerting the local residents on potential fire threats. These indices are derived from weather data like, temperature, rainfall, and the condition of vegetation recorded by local weather stations. Weather data often come from sparsely located weather stations. The drought indices derived from these point source weather data are then manually interpolated across the entire state based on an expert judgement at a coarse spatial resolution (county level). This procedure of calculating and interpolating drought indices across the entire state relies heavily on an expert judgement and involves lot of uncertainties. Further, high spatial resolution data is often needed for effective wildfire risk assessment and control.

During the past two decades several advances have been made in remote sensing and GIS technologies and high spatial resolution data is readily available for conservation and management of natural resources. Hence, weather data like temperature and rainfall needed for developing fire potential indices can be derived readily from remotely sensed data. The objective of this project is to develop fire risk index using weather data obtained from AVHRR (Advanced Very High Resolution Radiometer) satellite and NEXRAD (NEXt generation RADar) for Texas at a spatial resolution of 1km × 1km.

Keetch-Byram Drought Index (KBDI)

KBDI is being widely used by fire managers for monitoring moisture deficiency in the deep duff and upper soil layers. It is being widely used because of its simplicity and is the only drought index that relates the effect of drought with potential fire activities. KBDI is based on a simple single layer water balance model and indicates the amount of moisture depleted from the soil. The theory and framework of KBDI is based on the following assumptions (Keetch and Byram, 1968):

1. The rate of soil moisture loss depends on:
   - density of the vegetation cover
   - antecedent moisture conditions
   - annual rainfall
   - evapotranspiration
2. The field capacity of soil is 8 inches of available water (eight inches of water is chosen because in many areas of the country it takes all summer for the vegetation cover to transpire that much water. This number suites reasonably well for use in forest fire control).

Four climatological parameters are used to calculate KBDI. They are:

1. Daily maximum temperature
2. Daily rainfall
3. Cumulative antecedent moisture deficiency

4. Annual average precipitation.

Keetch and Byram (1968) explain in detail the mathematical formulations involved for computing KBDI. The result of this system is a number that represents the moisture deficiency in the upper soil layer in hundredth of an inch. A scale of 0 to 800 is used to represent the moisture deficiency with 0 being no moisture deficiency and 800 being the maximum possible moisture deficiency. These numbers are correlated with the fire potential as shown in table 1.

Table 1: KBDI and fire potential

KBDI	Fire potential
0 - 200	Low
200 - 400	Moderate
400 - 600	High
600 - 800	Very high

If the KBDI for a county is more than 500, countywide outdoor burning bans are imposed by Texas Forest Service (TFS) for preventing wildfire in that county.

Current Practice

Presently all the climatological data needed to compute KBDI are obtained from sixty ground based weather stations across Texas. Daily weather data for these stations are collected by the National Weather Service (NWS) and are available from their web site at http://iwin.nws.noaa.gov/iwin/tx/climate.html. These daily weather data are downloaded manually from NWS and imported into a spreadsheet for calculating daily KBDI. KBDI derived from these point data sources are then interpolated at a county scale across the entire state based on an expert judgement. Some of the uncertainties involved with this procedure are listed below:

- Localized precipitation events are very common in arid climatic zones. These precipitation events may not be captured by the sparsely located rain gauges.
- KBDI calculated using weather data from point source when interpolated across large regions could introduce errors.
- The interpolation method in use is based on human judgement. This might introduce bias while interpolating KBDI across large areas.

With advances in computational sciences the procedure for computing KBDI can be automated and spatial accuracy can be improved considerably (county scale to 1km × 1km) by using GIS and remote sensing technologies.

Proposed Methodology

The proposed methodology involves use of remote sensing data from AVHRR and NEXRAD for deriving weather parameters like maximum air temperature and 24hr rainfall.

Maximum Air Temperature

Maximum air temperature (T_a) needed for calculating KBDI was derived from land surface temperature (T_s) obtained from thermal channels of AVHRR satellite. [Land Surface Temperature (LST) is the temperature measured just few inches above the surface of the land or the vegetation]. AVHRR is a sensor aboard the National Oceanic and Atmospheric

Administration (NOAA) series of polar orbiting earth satellites that are in operation for more than three decades. NOAA series of satellites are the primary source for monitoring weather across the globe. AVHRR is a broadband scanner, sensing in the visible (Channel 1), near-infrared (Channel 2) and thermal infrared portions (Channel 3, Channel 4 and Channel 5) of the electromagnetic spectrum at a resolution of 1km × 1km. Currently NOAA - 14, 15 and 16 satellites are operational.

LST can be derived using a split window algorithm from channels 4 and 5 brightness temperatures. Several split window algorithms have been developed and used for deriving LST from channels 4 and 5, to account for the effects of atmospheric disturbances on the satellite measurements. The split window algorithm developed by Ulivieri et al. (1994) has been used in this study to derive LST from the thermal channels. As mentioned previously LST is different from the air temperature that is measured at a standard height of 2m. Maximum air temperature (T_a) can be obtained from the surface temperature (T_s) using an energy balance approach. But such an approach involves too many variables that cannot be readily derived from satellite measurements.

Hence a simple regression approach has been adopted for deriving T_a from T_s. Comparison of surface temperature obtained from the satellite and the maximum air temperature measured at weather stations across Texas show that there is a strong linear relationship between T_s and T_a. However this linear relationship varied spatially among weather stations across Texas even within the same climatic division [Texas is divided into ten climatic divisions (Fig. 1) by NWS based on the climatological parameters like temperature, precipitation, etc.,]. Hence long-term maximum air temperature (T_{lm}) obtained from 30 years of historical weather data was incorporated into the regression model to account for spatial variation in the relationship among weather stations. Incorporation of T_{lm} in the regression model reduced the spatial variation in the relationship among weather stations within a given climatic division. Since there are ten climatic divisions in Texas, one such regression model has been developed for each climatic division. The regression model adopted in the study is of the form:

$$\hat{T}_a(i) = m(i)\sqrt{T_s \times T_{lm}} + C(i) \qquad (1)$$

Where:

$\hat{T}_a(i)$ - estimated daily maximum air temperature for climatic zone i

T_s - land surface temperature (˚F)

T_{lm} - long-term monthly maximum air temperature (˚F)

m(i) and C(i) are regression constants for climatic zone I (where i = 1,…..10).

In this study daily weather data (September, 1999 to August, 2000) from 57 weather stations distributed across Texas were available for model development and validation (Fig.2). Daily weather data from 27 weather stations were used for model development and data from 30 weather stations were used for model validation. Comparison of model estimated $\hat{T}_a$ with that of the measured T_a (Fig. 3) show that the model estimated air temperatures are in good agreement with the measured air temperature (r^2 = 0.79 and slope ≈ 1).

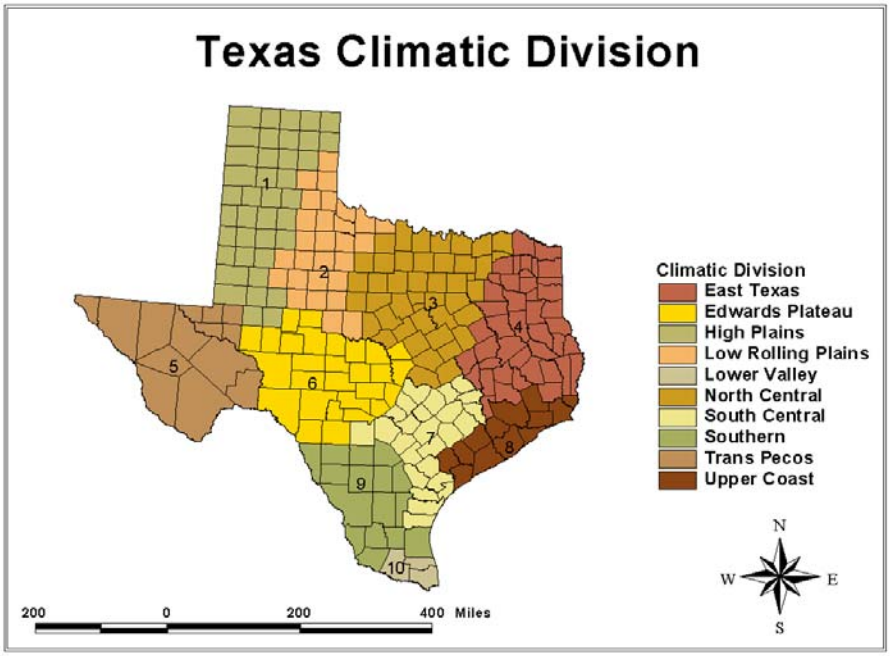

Figure 1. Climatic Divisions of Texas.

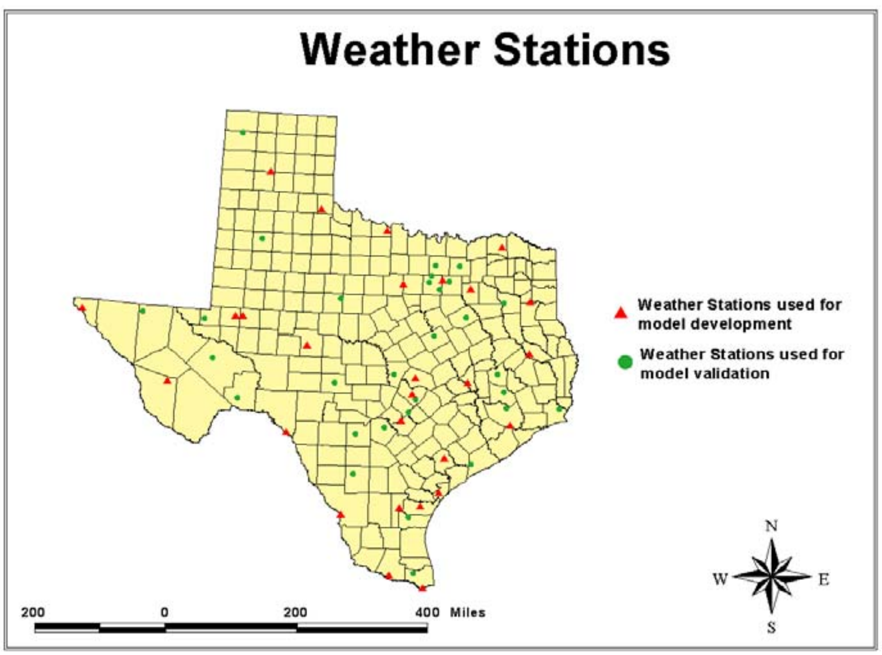

Figure 2. NWS weather stations used for model development and validation.

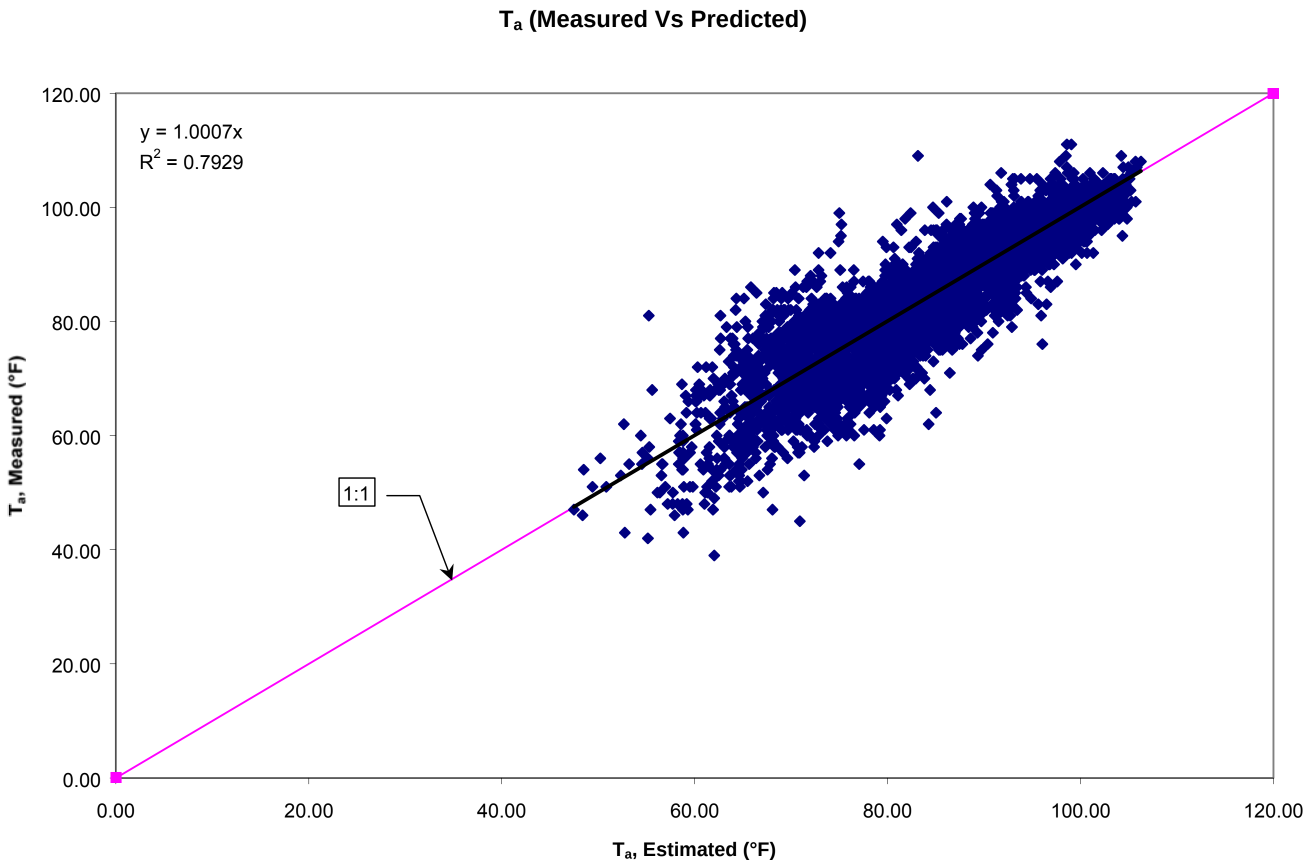

Figure 3. Comparison of model estimated air temperature with air temperature measured at NWS weather stations.

Daily Precipitation

Daily precipitation need for calculating KBDI was obtained from NEXRAD system of NWS. NEXRAD is a Doppler radar known as the Weather Surveillance Radar-1988 Doppler (WSR-88D). NEXRAD provide precipitation data for larger areas with better spatial and temporal resolution than conventional raingages. The processing of NEXRAD involves three stages. Jayakrishnan (2001) explains each processing stages of NEXRAD in detail.

Precipitation is a sensitive parameter in the estimation of KBDI. As mentioned before, localized precipitation events are very common in arid climatic zones. These precipitation events may not be captured by the sparsely located rain gauges. Since outdoor burning bans and distribution of fire personnel across the state depend on KBDI estimates, accurate estimation of KBDI is essential. NEXRAD provides best estimates of precipitation over large areas with high spatial resolution (4km × 4km). Hence by using remotely sensed temperature and precipitation estimates obtained from AVHRR and NEXRAD respectively, accurate estimation of KBDI is possible at a high spatial resolution.

Real-Time System

A real-time system (Fig. 4) has been developed for estimation of daily KBDI from remotely sensed data using Arc Macro Language (AML) in ARC/INFO (GIS software). The satellite receiving system located in Blackland Research Center (BRC), Temple, TX acquires daily raw AVHRR data from NOAA-14 and NOAA-15 satellites. An automatic data processing system has been developed using PCI (remote sensing software) for radiometric, geometric and atmospheric corrections and for computing NDVI (Normalized difference Vegetation Index) and LST. Besides these standard processing, algorithms developed by various researchers have been refined for cloud detection (Chen, 2001). During cloudy days (cloud cover > 30%) it may not be possible to get maximum air temperature estimates from AVHRR satellite. Hence, during cloudy days maximum air temperature measured at sixty NWS weather stations are used instead of satellite data. Maximum air temperature measured at sixty NWS weather stations across Texas is interpolated using “Regular Spline” method using ARC/INFO for KBDI estimation during cloudy days. An automatic data-capturing algorithm has been written using PERL and SHELL scripts for obtaining the daily maximum air temperature from 60 NWS weather stations (http://iwin.nws.noaa.gov/iwin/tx/climate.html).

The Stage III NEXRAD data is collected and archived by NWS. A MOU exists between BRC and NWS for obtaining this daily Stage III precipitation data from NEXRAD. The stage III data is in HRAP grid system and the rest of the data are in a regular grid system. Hence the precipitation data is remapped to the regular grid system using ARC/INFO. Once all the input data need for computation of KBDI is prepared, KBDI is computed using AML in ARC/INFO GIS software. The workflow of the developed real-time system is shown in fig. 4.

Conclusion

A real-time system has been developed for estimation of fire potential index (KBDI). Use of GIS and remote sensing technologies overcomes the uncertainties involved in the computation of KBDI. The spatial accuracy of KBDI estimates has also been improved (county scale to 1km × 1km) due to the use of remotely sensed data and GIS (figs. 5 and 6). Research work is in progress at Texas A&M University in coordination with TFS for evaluating the KBDI estimates derived from remotely sensed data to that of the KBDI derived using weather station data. Efforts are also underway for development of a new fire potential index by incorporating NDVI estimates with that of soil moisture deficit. NDVI gives a measure of greenness/dryness of vegetation. Since greenness or dryness of vegetation plays an important role in the ignition or spread of wildfire, this can give a better estimate of fire potential at a given place.

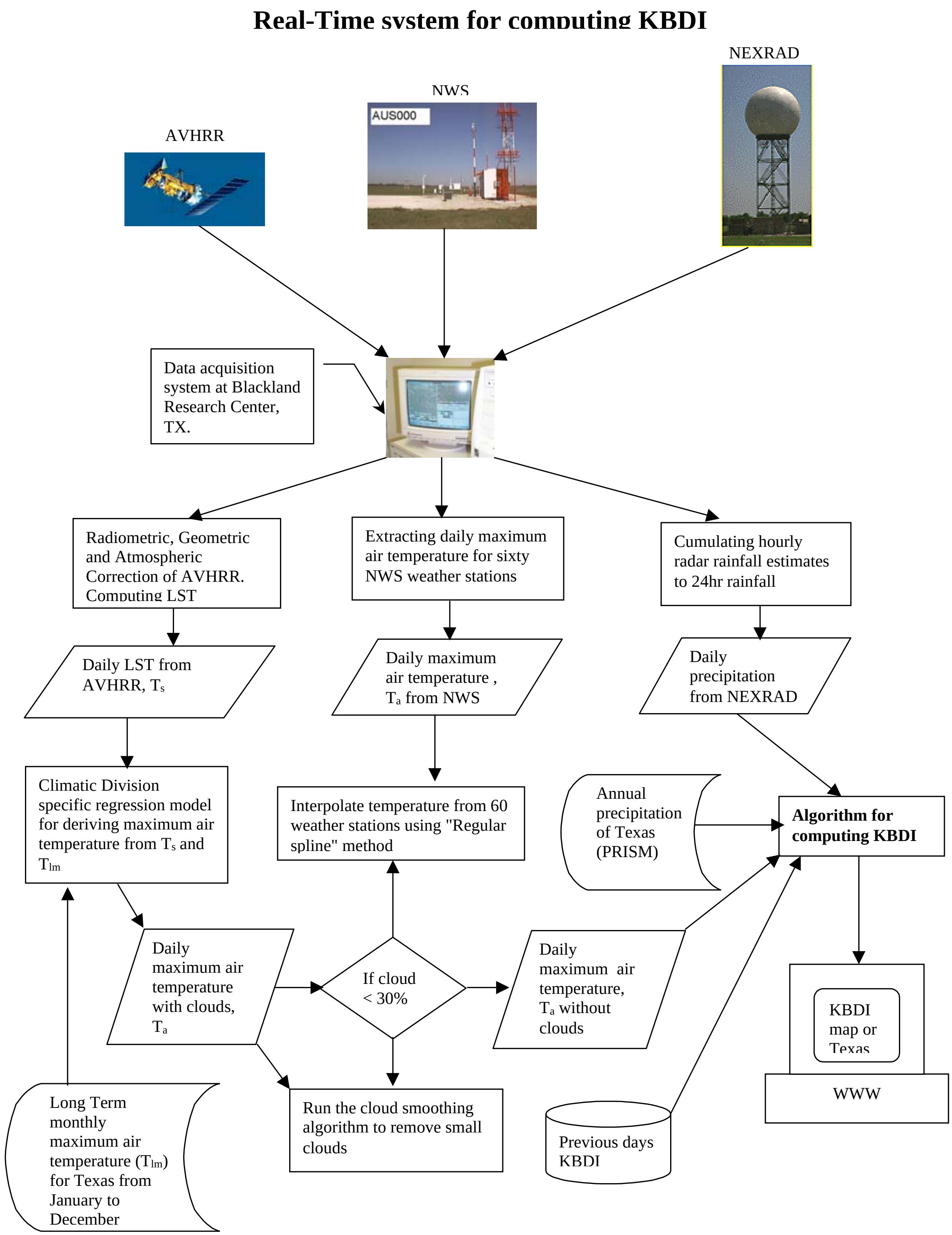

Figure 4. A real-time system for computing KBDI using remotely sensed data and GIS.

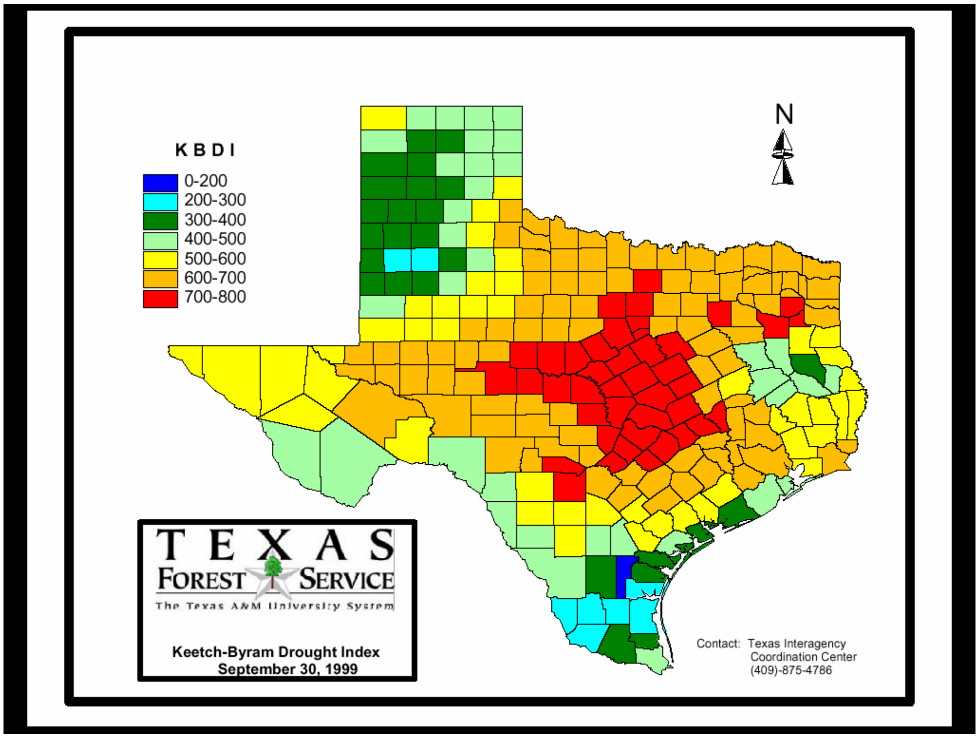

Figure 5. KBDI for September 30, 1999 computed by conventional method (Courtesy of TFS).

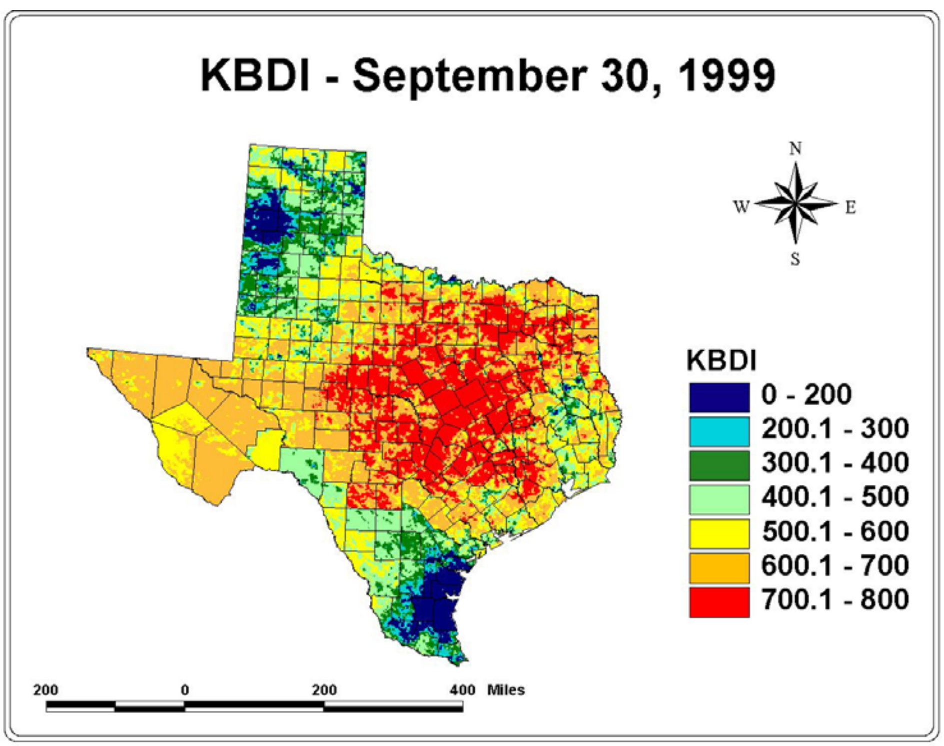

Figure 6. KBDI at a resolution of 1km $\times$ 1km computed using remotely sensed data.

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References

Chen, P. 2001. An Improved Cloud Detection Algorithm for Monitoring Agricultural Growing Conditions with NOAA AVHRR Data in Texas. Diss., Texas A&M University, College Station, p76.

Jayakrishnan, R. 2001. Effect of Rainfall Variability On Hydrologic Simulation Using WSR-88D (NEXRAD) Data. Diss., Texas A&M University, College Station, p158.

Keetch, J.J., and G.M. Byram. 1968. A Drought Index for Forest Fire Control, USDA Forest Service Research Paper No. SE 38, Asheville, NC.

Ulivieri, C., M. M. Castronouvo, R. Francioni, and A. Cardillo. 1994. A Split Window Algorithm for Estimating Land Surface Temperature from Satellites. Advances in Space Research. Vol. 14(3): 59 – 65.